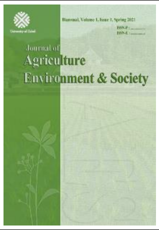
Agriculture, Environment & Society

Journal homepage: www.aes.uoz.ac.ir



Carbon sequestration in soybean agroecosystems

Samaneh Bakhshandeh [a], Hossein Kazemi [*a], Behnam Kamkar [b], Afshin Soltani [a]

[a] Department of Agronomy, Faculty of Plant Production, Gorgan University of Agricultural Sciences and Natural Resources (GUASNR), Gorgan, Iran
[b] Department of Agrotechnology, Ferdowsi University of Mashhad, Mashhad, Iran

ARTICLE INFO

Article history:
Received: 17 March 2023
Accepted: 06 May 2023
Available online: 05 June 2023

Keywords:
Carbon sequestration
DNDC model
SOC
Soybean

ABSTRACT

Today, the DeNitrification DeComposition (DNDC) is model used to anticipate soil organic carbon (SOC) turnover and crop growth under various field management practices. Gorgan County is an important region for soybean production in Iran. We aimed to 1) validate the DNDC model for modeling SOC dynamic in croplands under soybean cropping, 2) simulate the total topsoil (0–30 cm) SOC stocks of soybean cropping systems, 3) quantify the spatial distributions of carbon sequestration potential of soybean-grown croplands by Geographic Information System (GIS) techniques. In this research, soil samples were taken from 150 fields at depth of 0–30 cm before soybean cultivation and after crop harvesting. In this research, we used the site simulation type of DNDC model for simulation and denitrification/decomposition procedure. Inputs in the DNDC model included information on survey region, climate, soil, crop properties, and farmland management practices. The soil and crop properties categorized into farming management practices such as fertilization, tillage, grazing or plant cutting, and irrigation. The climatic data were obtained from one meteorological station located within the study area. To continue, crop parameters were provided based on field survey and laboratory work. Also, the soil properties (including texture, bulk density, pH, SOC, soil total N, field capacity, wilting point, hydro-conductivity point, porosity and clay fraction) were obtained from sampling sites distributed in soybean croplands of Gorgan county. Results indicated that the DNDC model can simulate the SOC values for soybean fields. Based on the results, there was correlation between the simulated and measured data for SOC. The average concentration and storage of carbon sequestration were as 3.97 and 1.42 Mg ha^{-1} for observed situation and in predicted situations obtained as 2.60, and 1.42 Mg ha^{-1}, respectively. The highest content of SOC was related to the east, southeast, and central parts toward the south of the county, which was affected by several factors such as soil bulk density, regional climatic condition, using conservation cropping systems, improved irrigation systems, and fertilization management type. The study provided new information on how improvements in the process-based DNDC model in Iran. Therefore, it can be utilized to determine SOC change and dynamism and carbon sequestration potential on the regional scale.

Highlights

- The spatial distribution of carbon sequestration potential was quantified using GIS techniques.
- The DNDC model was used for simulation, incorporating data on region, climate, soil, crop properties, and management practices.
- The DNDC model effectively simulated SOC values for soybean fields.
- The highest SOC content was observed in the east, southeast, and central parts of the county.
- The study provided new information on using the DNDC model for regional-scale SOC assessment in Iran.

[*] Corresponding author.
E-mail address: hkazemi@gau.ac.ir
https://doi.org/10.22034/jelsa.2024.458528.1065

1. Introduction

Croplands can be a source or sink of carbon dioxide (CO_2). CO_2 fluxes are often deduced based on the changes in measured carbon stocks (Mosier et al., 2006). A minor change in soil organic carbon (SOC) may cause significant changes in the concentration of atmospheric CO_2 (Schlesinger, 1984). Global carbon sequestration potential in croplands has been estimated to be of "40–60 Pg at the rate of 0.4-1.0 Pg C yr^{-1}, which is about 12–30% of the current rate of increase in the CO_2 atmospheric concentration (Lal and Bruce, 1999; Lal, 2004; Smith, 2004b). Carbon sequestration in croplands is a partial and short-term solution. Also, it is cost-effective, and critical for meeting the global climate targets. On the other hand, it buys time during which new technologies for carbon emission reduction or accumulation in other divisions could be developed (Lal, 2001, 2003; Smith, 2004a; Bajzelj et al., 2014).

Lokupitiya et al., (2009) believe to optimize the climate change mitigation and carbon sequestration potential in croplands, assessment, quantification, and evaluation of carbon balance and its components are required under crop type, management practices and rotation. However, some researchers believe that processed-based models are important tools to use as supplementary information to gap-fill incomplete measurements to capture the full carbon budget, evaluation of alternative management practices for improved carbon balance and assessing mitigation strategies under future scenarios (Grant et al., 2007; Smith and Smith, 2007; Wallach et al., 2014). Based on this viewpoint, different models have been developed to simulate carbon dynamics in different ecosystems particularly agroecosystems (Li et al., 1992; Li et al., 1994; Li., 2000).

The DeNitrification DeComposition (DNDC) model is one of the most widely admitted agroecosystem models in the world (Gilhespy et al., 2014). Hopeful performances of the DNDC model has been validated in Asia (Wang et al., 2013), Europe (Abdalla et al., 2011) and America (Tonitto et al., 2007). The DNDC model is midway and comparatively simple, and simulates detailed SOC dynamics, daily carbon exchange, carbon balance, and crop growth and production based on crop management, soil characteristics and climatic conditions (Gollany et al., 2012a; Zhang et al., 2015; Del Grosso et al., 2016).

The simulation results of the DNDC model reported by Zhang et al., (2016) showed a strong correlation between simulated and measured winter wheat SOC contents. Also, they reported that the DNDC model can be used to anticipate SOC turnover and crop growth under different fertilization and straw return conditions in the studied area. In other research, Yan et al., (2016) evaluated the simulated results with the SOC values found in Huantai county China, from 1982–2011 by the DNDC model.

They expressed that the simulated values were more consistent with the observed ones in the two different modeling parts. The simulated findings achieved by Hua-Jun et al., (2010) indicated that the total SOC storage and SOC density in the croplands of China were 4.7-5.2 Pg C, and 3.9 to 4.4 kg C m^{-2}, respectively, which these amounts were much lower than the world average level. In another study, the model results applied by Tang et al., (2006) revealed that the total SOC storage in croplands in China was about 3,968 Tg C; and SOC was lost at a rate of 78.89 Tg $Cyear^{-1}$. Based on these results and with regard to the potential of global warming, SOC loss in croplands could be a serious contributor. The strategies to reduce the SOC loss in croplands are suggested based on the DNDC model under different management practices and scenarios. For example, Zhang et al., (2015) demonstrated that SOC stocks in the semiarid regions in China amounted to 1.15 Pg C and the SOC content of 65% farmlands was below national average level.

Soybean, an oilseed crop, has many benefits that attracted much attention in Iran, typically in Golestan province. Gorgan County is one of the most important regions for soybean production in Golestan Province. In 2017, the total soybean cropping area and grain yield in this county were 11,200 ha and 2,400 kg ha^{-1}, respectively (Agricultural Organization of Golestan, 2018). This crop is suitable in the current rotation systems in Golestan province. Because of intensive farming in Gorgan county, there is a significant lack of specific information on the carbon sequestration potential of soybean in this region. Therefore, we aimed to 1) validate the DNDC model for modeling SOC dynamic in croplands under soybean cropping, 2) simulate the total topsoil (0–30 cm) SOC stocks of soybean cropping systems, (3) quantify the spatial distributions of carbon sequestration potential of soybean-grown croplands by Geographic Information System (GIS) techniques.

2. Materials and methods

2.1. Study area

The research area was located in the Gorgan county in Golestan province, north of Iran. The region coordinates range from 53° 57′ and 56° 32′ E longitudes and 36° 30′ and 38° 8′ N latitudes (Figure 1). Gorgan has a semi-Mediterranean and semi-humid climate with a mean annual rainfall of 422.5 mm per year (Golestan Province Meteorological Office, 2016). This county borders by Aq-Qala County by the north, Semnan Province by the south, Kordkouy County by the west and AliAbad Katool County in the east. In Gorgan county, soybean is sown during May and June and is harvested in October and November every year.

2.2. Selected fields and data collection

In this research, the croplands of the Gorgan county as an important region for soybean production in Iran were selected as studied areas. The surveyed fields were selected in four main directions of the county with a regular distribution in agricultural areas under soybean cultivation. All geographic coordinates of sampling fields were recorded by a GPS, model Garmin 60. The location of sampling sites showed in Figure 2. Soil samples were taken from 150 fields at depth of 0–30 cm before soybean sowing and after crop harvesting, during 2017.All soil samples transported to the crop research laboratory of Gorgan

University of Agricultural Sciences and Natural Resources (GUASNR), then air-dried to remove stones and coarse plant residues. Then,organic carbon storage was calculated by the Eq. 1(Lema et al.,2006):

$$SCS = SOC \times BD \times H \times 10 \quad (1)$$

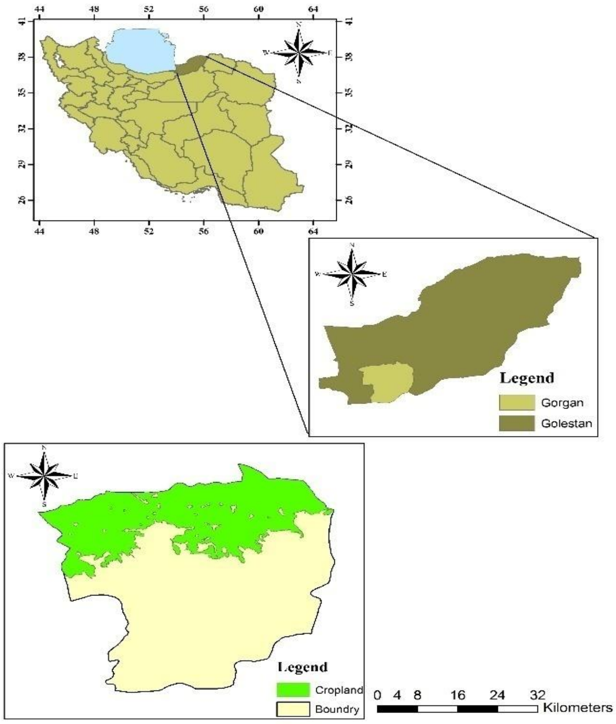


Figure 1. The location of Gorgan county in Golestan province, Iran.

Where, SCS is the soil organic carbon storage (Mg ha^{-1}), SOC is the soil organic carbon content (g kg^{-1}), BD is the soil bulk density (Mgm^{-3}), H is the thickness of the soil layer (m), and 10 is the coefficient for converting Mg m^{-3} into Mg ha^{-1}. In this research, soil texture and pH were obtained by the hydrometry method and pH meters, respectively. Also, soil bulk density (BD) was determined by Archimede's method (Blake and Hartge, 1986). Also, the Walkley and Black method was used to determine the carbon contents of samples (Walkley and Black, 1934; Nelson et al., 1996). Finally, carbon sequestration was calculated by Eq. 2 (Li et al., 2016)**:**

$$CSeqsoil = SOC_{after} - SOC_{before} \quad (2)$$

Where, *CSeqsoil* is the soil carbon sequestration, SOC_{before}; organic carbon content in the soil before soybean sowing and SOC_{after}; organic carbon content in the soil after soybean harvesting.

Also, plant samples were randomly taken from selected fields based on W-shaped pattern by 0.5×0.5 m^2 quadrate. In the final sampling, total plant samples transported to the crop research laboratory of GUASNR, then oven-dried at 70 °C for 48 h and weighed.

2.3. DNDC model

2.3.1. Description of the model

In the DNDC model, the first part has three sub-models including soil organic matter decomposition, soil climate, and crop growth. It simulates the soil environmental condition according to ecological driving factors. The second part is made up of three sub-models including nitrification, denitrification, and fermentation. This part simulates the effects of the soil environmental condition on microbial activity and corresponding dynamic change of soil carbon and nitrogen (Li, 2001). The DNDC simulates SOC dynamics by quantifying the turnover of four major SOC pools including microbial biomass, plant residue, active humus, and passive humus (Pathak et al., 2005). This model can describe the interactions between the driving factors. Therefore, it can simulate the carbon and nitrogen biogeochemical cycle (Li, 2007).

2.3.2. Model inputs

Inputs in the DNDC model included information on survey region, soil, climate and crop properties. The soil and crop properties categorized into farming management practices such as fertilization, irrigation, tillage, and grazing or plant cutting. The DNDC model runs in two forms: region simulation type and site simulation type. In this research, we used the site section for simulation and denitrification/decomposition procedure. Therefore, the input parameters included meteorology, soil, crop and farmland management practices data. The details of these inputs were listed in Table 1. The data of farmland management practices was collected by in-person interviews with 150 farmers in Gorgan county. This data included straw incorporation, fertilizer date, fertilizer applied amounts, and irrigation date and amounts. Also, some required data such as soybean growing season, planting date, harvesting date, and cropping rotation collected from the Agricultural Organization of Golestan province.

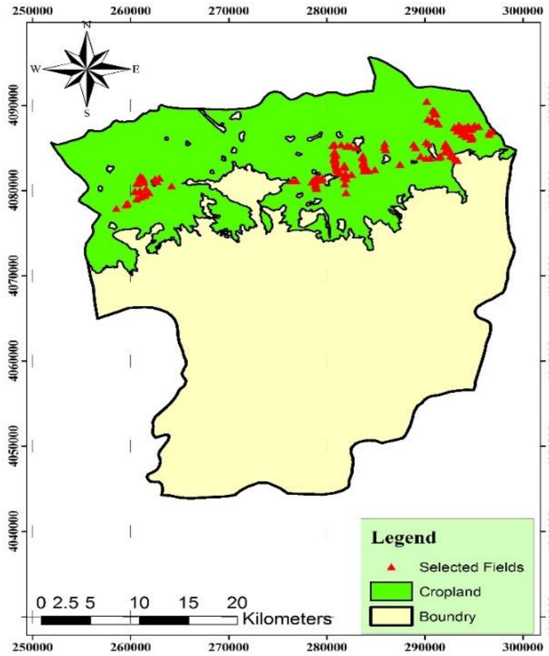


Figure 2. The location of the selected fields in Gorgan county, Golestan province, Iran.

In this research, climatic data were obtained from one meteorological station located within the study area (Hashem Abad station). N concentration in rainfall, atmospheric background NH_3 concentration, atmospheric background CO_2 concentration and annual increase rate of atmospheric CO_2 concentration were considered as climatic parameters in this model. These parameters were obtained from Golestan Meteorology Organization (2017) and NOAA site (http://www.noaa.gov).

In this research, crop parameters were provided based on a field survey and laboratory works (Table 1). All plant samples were separated and measured based on the dry matter weight in the laboratory of the GUASNR. Finally, the soil properties data were obtained from sampling sites distributed in soybean croplands of Gorgan county, including soil texture, pH, bulk density, SOC, field capacity, soil total N, hydro-conductivity point, wilting point, porosity and clay fraction.

Table 1. Main parameters used in the denitrification/decomposition model (DNDC) for the site simulation type

Type	Details
Climate	Latitude (o) N concentration in rainfall (mg L-1) Atmospheric background NH3concentration (mg kg-1) Atmospheric background CO2 concentration (mg kg-1) Annual increase rate of atmospheric CO2concentration (mg kg-1)
Soil	Texture Bulk density (g cm-3) pH Field capacity Wilting point Clay fraction Hydro-conductivity (m h-1) Porosity SOC (g kg-1) Soil total N (g kg-1)
Crop	Maximum biomass (kg C ha-1) Biomass fraction Biomass C/N ratio Total N demand (kg N ha-1) Thermal degree days Water demand (g water g-1dry matter) Tilling date (month-day) Tilling method
Farming management practice	Planting date/Harvest date (month-day) Straw incorporation Fertilizer date (month-day) Fertilizer applied amount (kg ha-1) Irrigation date (month -day) Irrigation amount (mm)

2.3.3. Model validation

In order to the validation of the DNDC model, some statistics were evaluated. These included correlation coefficients (r), root mean square error (RMSE), mean absolute error (MAE), mean bias error (MBE) and model efficiency (EF). Usually, the correlation coefficient is the correlation degree between the simulated against observed values, and its significance was calculated according to the T-test. Also, the accuracies of the simulations were estimated using the other mentioned statistics. The lower values of RMSE, MAE, and MBE indicate the lower difference between the simulated and observed data. Also, the EF equal with 1 value, indicates a better significant correlation between the predicted and observed data (Webster and Oliver, 2000; Mishra et al., 2010; Wang et al., 2013). The statistics were calculated as follows:

$$\mathrm{RMSE} = \sqrt{\sum_{i=1}^{n}[(p_i - O_i)]^2 / n} \quad (3)$$

$$\mathrm{MAE} = \frac{\sum_{i=1}^{n}|p_i - O_i|}{n} \quad (4)$$

$$\mathrm{MBE} = \frac{\sum_{i=1}^{n}(p_i - O_i)}{n} \quad (5)$$

$$r = \frac{\sum_{i=1}^{n}(P_i - \bar{P}) \times (O_i - \bar{O})}{\sum_{i=1}^{n}\sqrt{(P_i - \bar{P})^2} \times \sum_{i=1}^{n}\sqrt{(O_i - \bar{O})^2}} \quad (6)$$

$$\mathrm{EF} = 1 - \frac{\sum_{i=1}^{n}(P_i - O_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2} \quad (7)$$

$$\mathrm{CV} = \frac{\mathrm{RMSE}}{\bar{O}} \quad (8)$$

Where, P is the mean of the predicted values, P_i is the predicted values, $\bar{O}$ is the mean of the observed values, O_i is the observed values and n is the number of paired values (i=1, 2…, n) (Mishra et al., 2010; Álvaro-Fuentes et al., 2012; Wang et al., 2013).

2.4. GIS procedures

The DNDC model input values for soil properties, daily weather, crop rotations, and agronomic management practices collected from various sources and organized as databases by Geographic Information System (GIS) techniques (Xu et al., 2012). In this study, the spatial distribution of predicted data by DNDC and observed data were interpolated by different geostatistical and classic interpolation procedures such as Inverse Distance Weighted (IDW), Ordinary Kriging (OK), Local Polynomial Interpolation (LPI) and Radial Basis Functions (RBF) in ArcMap software, ver.10.6. For this purpose, we used the geostatistical analyst tools in ArcMap. All layers were georeferenced to UTM (WGS-84) coordinate system. Then, the thematic layers were produced in ArcGIS media.

3. Results and Discussion

3.1. DNDC model validation

The long term data from a metrological station located in Gorgan county was used to validate the DNDC model in this study. For model validation, we used the simulated and measured SOC changes. Results showed that the correlation coefficients between the simulated values and field values for SOC content and carbon stock in Gorgan county were 0.99 and 0.99 for before soybean planting stage, and 0.98 and 0.98 for after harvesting stage, respectively. These values were significant at the 0.01 probability level (Table 2).

Therefore, these results showed that there was correlation between the simulated and measured data of SOC (Figure 3). Also, the values of RMSE for the simulation of the SOC content and stock were as 2.56 and 0.31 in before planting stage and 0.89 and 0.28 for after harvesting stage, respectively. The values of model efficiency (EF) were obtained as 0.88 (SOC) and 0.84 (carbon stoke) (Table 2).

The best agreement between DNDC simulated and observed data was found in SOC stock after harvesting, where RMSE was 0.89 (Table 2). These results indicated that the DNDC model can successfully simulate the values of SOC for the soybean fields of Gorgan County. Previously, some researchers used this model for the estimation of SOC change under farming practices. For example, the results of Wang et al. (2013) showed that there was a strong correlation (R^2=99) between the simulated and measured data of SOC. Also, Yan et al., (2016) conducted validation of the DNDC model against field data sets of SOC from Quzhou Huantai County (China). They achieved high accuracy in the model simulation with the improvement of the model parameters. Based on the above validations, we can confirm that this model has an appropriate performance for the SOC change undercurrent soybean croplands in Golestan province.

Table 2. Values of some statistics for DNDC model validation

Variable	r	RMSE	CV	MBE	MAE	EF
SOC Stock- Before Planting (0-30 cm)	0.99**	2.56	8.33	2.48	2.48	0.73
SOC Stock- After harvesting (0-30 cm)	0.98**	0.89	2.54	0.038	0.620	0.95
OC- Before Planting (0-30 cm)	0.99**	0.31	2.28	0.129	0.265	0.97
OC- After harvesting (0-30 cm)	0.98**	0.28	1.91	0.016	0.14	0.96
Variable	**r**	**RMSE**	**CV**	**MBE**	**MAE**	**EF**
SOC Stock- Before Planting (0-30 cm)	0.99**	2.56	8.33	2.48	2.48	0.73
SOC Stock- After harvesting (0-30 cm)	0.98**	0.89	2.54	0.038	0.620	0.95
OC- Before Planting (0-30 cm)	0.99**	0.31	2.28	0.129	0.265	0.97
OC- After harvesting (0-30 cm)	0.98**	0.28	1.91	0.016	0.14	0.96

**; Significant in 1% probability level

3.2. Distribution of annual SOC change in soybean croplands

The average of SOC stock was increased in the soils under soybean cropping (Table 3). It was simulated from 31.13 to 33.74 Mg ha^{-1} for before planting and after harvesting, respectively. These amounts were observed as 28.27 Mg ha^{-1} for before planting and 32.26 Mg ha^{-1} for after soybean harvesting. These results confirmed that soybean croplands in Gorgan county can be a sink of carbon. Therefore, we can increase the SOC in soybean croplands by performing some methods and systems such as conservation agriculture, intercropping systems, crop residue mulching, ley-farming rotation, and organic farming. In similar research, the DNDC model findings indicated that the annual loss of SOC storage highly varied among the cropping systems. For example, the annual SOC losses in soybean fields (3.46 t C ha^{-1}) were two times higher than soybean-maize rotation fields (1.59 t C ha^{-1}) (Han et al., 2005).

3.3. Spatial distribution of SOC change

The spatial distribution of SOC change (0–30 cm) for soybean fields in Gorgan county was provided using ArcGIS software, var**.** 10.6. These amounts were predicted by the DNDC model.

3.3.1. Observed and simulated SOC; before soybean planting

Some interpolation methods, such as Local Ordinary Kriging, Radial Basis Functions, Polynomial Interpolation, and Inverse Distance Weighted were selected to provide a spatial layer of SOC. Results showed that Ordinary Kriging was the best method for interpolation of observed and simulated SOC. This model had the lowest error and the highest accuracy than other methods.

Based on the map produced by the Ordinary Kriging in ArcGIS software, the highest amount of observed SOC was obtained in the east, southeast and partly northeast of the region (Figure 4). It seems that because of the preservation of previouscrop residues (wheat) and increasing soil organic matter and also, reducing bulk density and increasing soil porosity, the soybean fields in these regions had generally the higher SOC than other regions. Also, the lowest amount of observed SOC was estimated in the central and southwest regions of Gorgan county (Figure 4).

Based on the map generated in ArcGIS software, the highest amount of simulated SOC was observed in the southeastern, central, and south areas of Gorgan county (varied from 30.43 – 33.29 Mg ha^{-1}). Also, the lowest amount of simulated SOC was simulated in the north and west regions (27.55- 30.43 Mg ha^{-1}).

Results of soil analysis showed that content of organic matters in these regions were lower than other areas in before soybean planting stage. The findings by Xu et al. (2012) demonstrated that the Spatio-temporal dynamics of SOC in China can be characterized by relating the DNDC outputs to the soil polygon-based database. Also, Lenka and Lal (2013) demonstrated that crop straw incorporation, animal manure application, and no-/reduced tillage were the most effective measures for increasing the SOC level. For example, straw incorporation can offer a substantial contribution to improve SOC by adding exogenous organic carbon to farmlands (Freibauer et al., 2004; Lugato et al., 2006). In another study, Jin et al., (2010) concluded that the effect of straw incorporation in combination with animal manure on increasing the SOC content was better than a high rate of straw return alone. Overall, the simulation accuracy of SOC was affected by the sensitive factors such as temperature, precipitation, soil bulk density, texture, and fertilization. Also, other factors, including rainfall N and atmosphere background NH_3, had a weak influence on SOC dynamic change. It seems that more precise regional parameters need to be provided to achieve higher simulation accuracy for the SOC through the DNDC model.

3.3.2. Observed and simulated SOC; after soybean harvest

Results showed that Ordinary Kriging was the best method for interpolation of observed and simulated SOC. This model had the lowest value of RMSE than other interpolation methods. After soybean harvesting in Gorgan county, the observed amount of SOC in measured fields was estimated between 32.21-35.95 Mg ha^{-1}. The highest content was observed in the eastern, southeast, and central parts toward the south of the county, which was affected by several factors such as soil bulk density, regional climatic conditions, performance of conservation cropping systems, modern irrigation systems, and fertilization management type (Figure 6). Hua-Jun et al., (2010) indicated that crop biomass production with relevant farming management practices plays an important role in affecting the carbon dynamics for agroecosystems. In this research, results showed that the amount of observed SOC decreases from eastern regions towards west regions of the county. In these regions, the amount of SOC ranged from 27.50-32.21 Mg ha^{-1}(Figure 5).

The model outputs indicated that the highest amount of SOC was simulated in the east, northeastern, and southeast areas of Gorgan county. This amount was estimated as 33.59 - 35.46 Mg ha^{-1}. Also, SOC content reduced from southern regions towards the north and southwest regions (Figure 5). In this regard, Chen et al., (2018) confirmed that the DNDC was an acceptable model for simulating SOC stock in Yucheng County (China).

According to the simulated results reported by Hua-Jun et al., (2010), the total SOC storage in China was 4.7-5.2 Pg C (0-30 cm) in 2003, with an average of 4.95 Pg C. In addition, SOC density in croplands of China ranged from 3.9 to 4.4 kg C m^{-2}, and this amount which was much lower than the world average (12.1 kg C m^{-2}). Principally, a variable may be homogeneous at one scale and heterogeneous at another, and information is often lost as spatial data are considered at small scales (Xu et al., 2013). Accordingly, Han et al., (2005) concluded that SOC values in the cropping systems attributed to either the land-use history or farming management.

Some researchers emphasized that climate change and soil conditions could play a role in the long-term SOC change. For example, Paul et al., (2002) observed that SOC accumulation increases with increasing annual rainfall. Also, the potential carbon sequestration is significantly different across the soil groups (Luo et al., 2010).

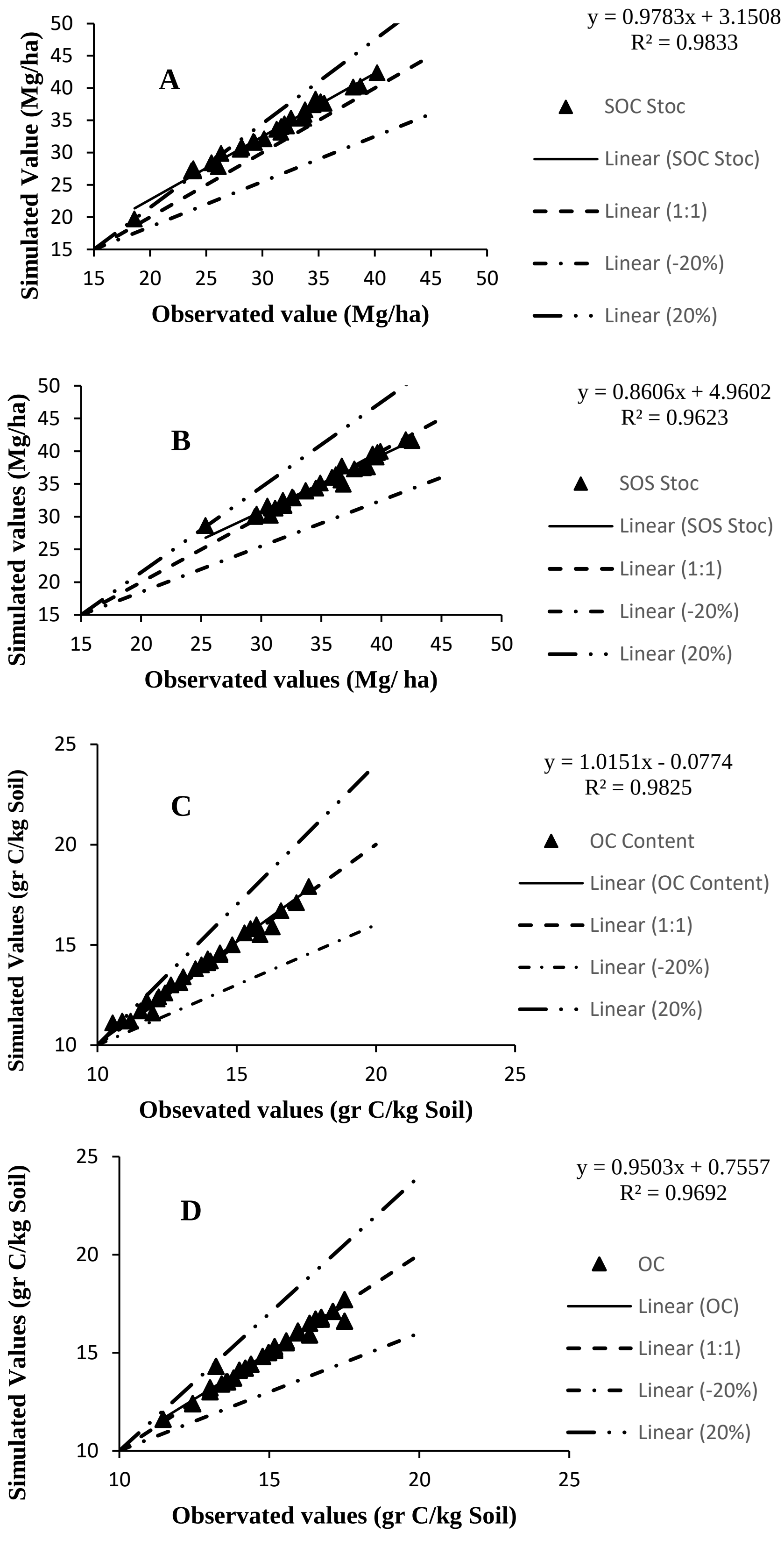


Figure 3. Simulation of SOC contents(0-30cm) in soybean croplands of Gorgan county, Iran; A) SOC stock (Mg ha^{-1}) in before planting, B) SOC stock(Mg ha^{-1}) in after harvesting, C) OC content (gr C kg^{-1} soil)in before planting, D) OC content (gr C kg^{-1} soil) in after harvesting.

Table 3. **Mean of SOC stock and SOC content for before planting and after harvesting stages in soybean fields, Gorgan County, Golestan Province.**

Variable	Depth(cm)	Before planting		After harvesting	
		Simulated	Observed	Simulated	Observed
SOCstock (Mg ha^{-1})	0-30	31.13	28.27	33.74	32.26
SOC content(gr Ckg^{-1}soil)	0-30	12.83	12.55	14.04	13.97

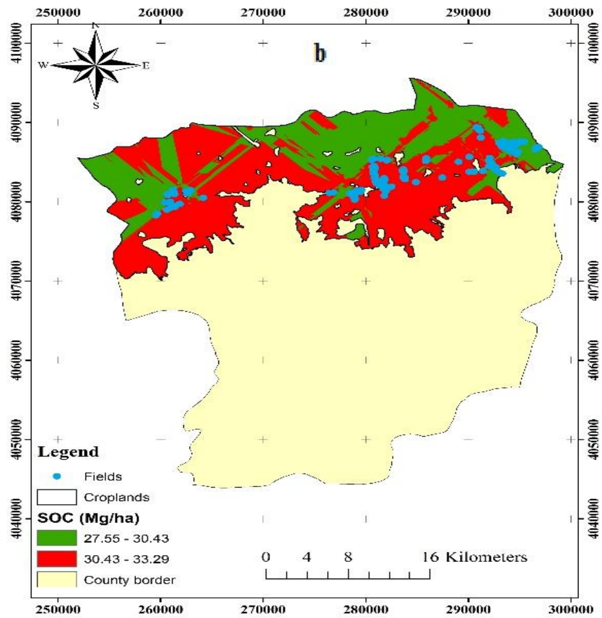


Figure 4. Maps of SOC in croplands of Gorgan county in before soybean planting: a) observed b) simulated values.

Table 4. Mean of CS-SOS and CS-OC in the soil of soybean fields, Gorgan, Iran.

CS- SOC (Mg ha^{-1})		CS- OC (gr c kg^{-1}soil)	
Simulated	Observed	Simulated	Observed
2.60	3.97	1.21	1.42

CS- SOC= Carbon Sequestration in Soil total organic C content (Mg ha^{-1}) (depth of 0-30 cm)
CS- OC= Carbon Sequestration in Organic Carbon Content (gr c kg^{-1} soil) (depth of 0-30 cm)

Table 5. Mean of dSOC, DOC and NEE simulated by DNDC model in the soil of soybean fields, Gorgan, Iran.

Stage	dSOC	DOC	NEE
Before planting	-1.18359	157.0035	-13.9894
After harvest	-1.28993	166.2731	-13.8232

dSOC= Daily change in SOC content (kg C ha^{-1} day^{-1}) (depth of 0-30 cm)
DOC= Soil dissolved organic C content (kg C ha^{-1}) (depth of 0-30 cm)
NEE= Net ecosystem C exchange rate (kg C ha^{-1} day^{-1}) (depth of 0-30 cm)

3.4. Carbon sequestration

The average concentration and storage of carbon sequestration in the observed and predicted state were as 3.97, 1.42 and 2.60, 1.42 Mg ha^{-1}, respectively (Table 4). These results demonstrate changes in carbon stock in the observed condition. Xu et al., (2012) demonstrated that Chinese paddy soils sequestered as 5.0 Tg C year^{-1}. Based on our results, in some soybean fields, carbon content decreased. Principally, this means that some soil carbon content was emitted as gas to the atmosphere. This rate depends on the tradeoff between crop residue and organic manure and losses of carbon by predominantly heterotrophic respiration associated with SOC decomposition (Li et al., 1997; Zhang et al., 2007; Gollany et al., 2010). Generally, soils should be managed according to their spatial distribution of carbon sequestration potential under different groups. In this study, the rate of dSOC† and NEE‡ were higher before the sowing stage than after the soybean harvesting stage. Also, the simulated and measured values of these parameters were completely similar (Table 5).

Some researchers reported that due to the complexity of carbon turnover processes and the dynamic response of carbon to environmental conditions, process-based models can extensively use to simulate the dynamics of SOC in agricultural systems (Paustian and Álvaro-Fuentes, 2011;

† - Daily change in SOC content

‡ - Net ecosystem C exchange rate

Gottschalk et al., 2012; Goglio et al., 2014). Hua-jun et al (2010) found that the annual SOC losses in soybean fields (3.46 t C ha^{-1}) were two times higher than those in soybean-maize rotation fields (1.59 t C ha^{-1}). The annual net changes in SOC storage ranged from + 0.19 to -73.6 Tg C yr^{-1} with a mean value of 36.7 Tg C yr^{-1}, or a loss of 0.7%. Approximately 92.6% of the soybean soils sequestrated C, while 5.3% lost C and only 2% kept balance in the soybean growing season.

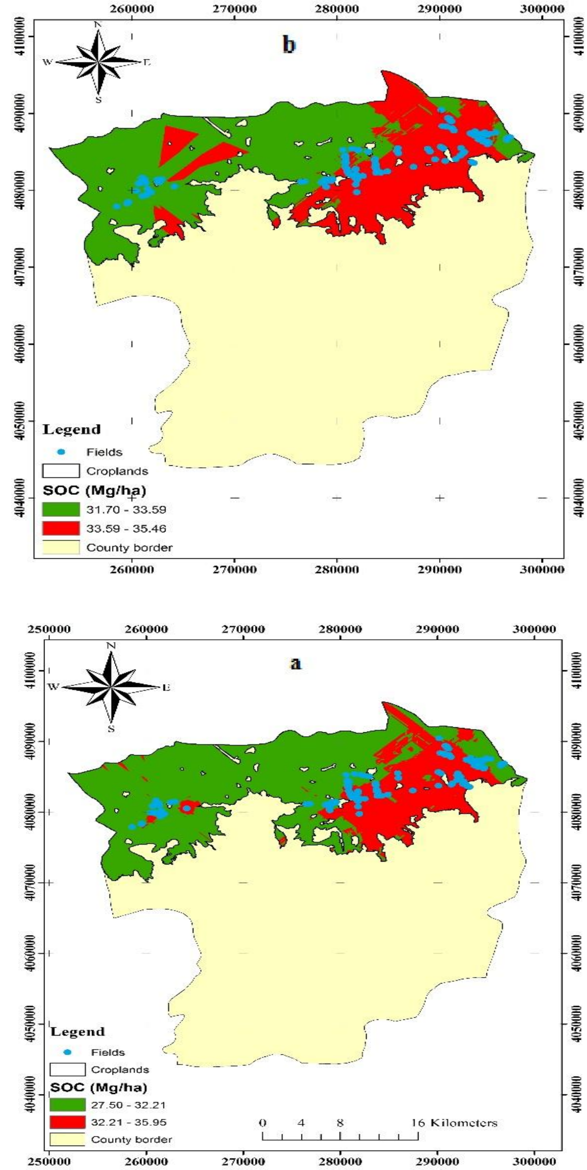


Figure 5. Maps of SOC in cropland of Gorgan county in after soybean harvest: a) observed b) simulated values.

3.4.1. Carbon sequestration; Observed

Some interpolation methods, such as Ordinary Kriging, Radial Basis Functions, Local Polynomial Interpolation, and Inverse Distance Weighted were selected to provide a spatial layer of carbon sequestration in Gorgan County. Results showed that Ordinary Kriging was the best method for interpolation of observed carbon sequestration. The highest carbon sequestration density was observed in the east and southeast of Gorgan county (4.34 – 6.95 Mg ha^{-1}). Also, the lowest carbon sequestration SOC was obtained in the central, west and southwest regions of the county (3.08–4.34 Mg ha^{-1}) (Figure 6). In this regard, the spatial distribution of SOC density in China revealed a sharp contrast between the northern and southern counties due to the differences in climatic conditions and farm management practices (Hua-jun et al., 2010).

Results showed that soybean fields with low soil bulk density and maintaining of residues in the soil surface had the highest carbon sequestration. The results highlighted the importance of crop straw incorporation, organic manure and optimized mineral fertilization on the carbon sequestration in the soybean croplands of Gorgan county.

Follett (2001) found that enhancing nutrient and water use efficiency can improve soil characteristics and microbial activity, following by increasing the carbon sequestration potential in fields.

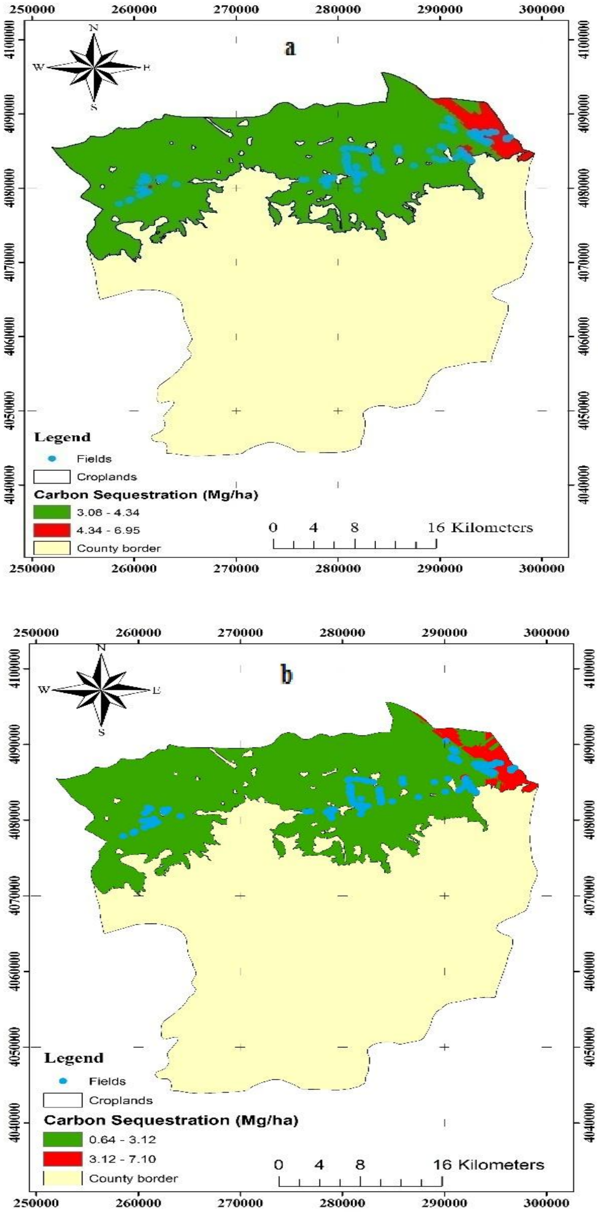


Figure 6. Maps of carbon sequestration in soybean croplands of Gorgan county; a) observed, b) simulated values.

3.4.2. Carbon sequestration; Simulated

Results showed that Ordinary Kriging was the best method for interpolation of simulated carbon sequestration in this study. The model output indicated that the highest amount of carbon sequestration was simulated in the east, northeastern, and north areas of Gorgan county. This amount was estimated as 3.12–7.10 Mg ha^{-1}(Figure 6). In this region, field management was performed very well by farmers than other regions of Gorgan county. Moreover, crop residues maintained in the field surface could increase the carbon sequestration contents in soil. Also, results showed that the carbon sequestration amount was reduced from east regions towards west regions (Figure 6). In the mentioned regions, some farmers usually burned the residues after harvesting the crops. This work can extremely reduce the microbial activity of soil and reduce the biodiversity in the surface soil and subsoil of croplands. The decrease in SOC storage leads to the decline of soil fertility and hence threatens agroecosystem sustainability. The difference between the SOC losses is essentially related to farming management practices (Han et al., 2005).

The study provided new information on how improvements in the process-based DNDC model in Iran. Therefore, it can be utilized to determine SOC change and dynamism and carbon sequestration potential on the regional scale.

4. Conclusion

Most of the information available about carbon sequestration is restricted to farm methods and analysis in Iran. The study reported in this paper provided new information on how improvements in the process-based DNDC model in this country can be utilized to explicitly determine SOC change and carbon sequestration on the regional scale. Results showed that there was a strong correlation between the simulated and measured data of SOC. The average concentration and storage of carbon sequestration in the observed and predicted state were as 3.97, 1.42 and 2.60, 1.42 Mg ha^{-1}, respectively. The highest carbon sequestration density was observed in the east and southeast of Gorgan county. The DNDC simulation results indicated that the SOC content of soybean croplands could be effectively increased when conservation of agricultural system, sewage sludge amendments, organic manure, ley-farming rotation, cover crops, organic farming systems, crop residues mulch, and intercropping systems are involved. Also, some farmers usually burn the residues after harvesting crops in Gorgan croplands and other regions in Iran. We recommend similar studies using different scenarios such as burn/ un-burn of crop residues, different crop rotations, and tillage system types. Based on results, we can confirm that DNDC model has an appropriate performance for the SOC change undercurrent soybean croplands. Also, we suggest preparing some hybrid sub-models with GIS program for the future.

Acknowledgment

This study has been supported by the grant approval of the Gorgan University of Agricultural Sciences and Natural Resources (GUASNR), Iran and the authors would like to appreciate it.

References

Abdalla, M., Kumar, S., Jones, M., Burke, J. & Williams, M. (2011). Testing DNDC model for simulating soil respiration and assessing the effects of climate change on the CO_2 gas flux from Irish agriculture. *Global and Planetary Change, 78*, 106–115. **doi:10.1016/j.gloplacha.2011.05.011**

Agricultural Organization of Golestan County. (2018). Agricultural statistics yearbook of 2017-2018. Statistic and Information Center.

Álvaro-Fuentes, J., Morell, F.J, Plaza-Bonilla, D., Arrúe, J.L. & Cantero-Martínez, C. (2012). Modelling tillage and nitrogen fertilization effects on soil organic carbon dynamics. *Soil and Tillage Research*, *120*, 32–39. **doi: 10.1016/j.still.2012.01.009**

Bajzelj, B., Richards, K.S., Allwood, J.M., Smith, P., Dennis, J.S., Curmi, E. & Gilligan, C.A. (2014). Importance of food-demand management for climate mitigation. *Nature Climate Change*, *4*, 924–929. **doi: 10.1038/nclimate2353**

Blake, G.R. & Hartge, K.H. (1986). Bulk density. In: Klute, A. (Ed). Methods of soil analysis. Part I: Physical and Mineralogical Method, Agronomy Monograph No. 9. ASA-SSSA, Madison, pp:363-375.

Chen, ZH., Wang, J., Deng, N., LV, CH., Wang, Q., Yu, H. & Li, W. (2018). Modeling the effects of farming management practices on soil organic carbon stock at a county-regional scale. *Catena*, *160*, 76-89. **doi: 10.1016/j.catena.2017.09.006**

Del Grosso, S.J., Gollany, H.T. & Reyes-Fox, M. (2016). Simulating soil organic carbon stock changes in agro-ecosystems using CQESTR, DayCent, and IPCC Tier 1 Methods. In: Del Grosso, S., Ahuja, L., Parton, W. (Eds.), Synthesis and Modeling of Greenhouse Gas Emissions and Carbon Storage in Agricultural and Forest Systems to Guide Mitigation and Adaptation. Advances in Agricultural Systems Modeling. In: Lajpat R. Ahuja (Ed.), Series Editor, vol. 6. **doi: 10.2134/advagricsystmodel6.2013.0001.5**. pp. 89–110

Follett, R.F. (2001). Soil management concepts and carbon sequestration in cropland soils. *Soil and Tillage Research*, *61*, 77–92. **doi: 10.1016/s0167-1987(01)00180-5**

Freibauer, A., Mark, D.A. & Smith, P. (2004). Carbon sequestration in the agricultural soils of Europe. *Geoderma*, *122*, 1-23. **doi: 10.1016/j.geoderma.2004.01.021**

Gilhespy, L.S., Anthony, S., Cardenas, L., Chadwick, D., del Prado, A., Changsheng Li, Ch., Misselbrook, T.M. Rees, R., Salas, W., Sanz-Cobena, A., Smith, P., Tilston, E.L., Topp, C.F.E., Vetter, S. & Yeluripati, J.B. (2014). First 20 years of DNDC (DeNitrification DeComposition): Model evolution. *Ecological Modelling*, *292*, 51-62. **doi: 10.1016/j.ecolmodel.2014.09.004**

Goglio, P., Grant, B.B., Smith, W.N., Desjardins, R.L., Worth, D.E., Zentter, R. & Malhi, S.S. (2014). Impact of management strategies on the global warming potential at the cropping system level. *Science Total Environnent*, *490*, 921-933. **doi: 10.1016/j.scitotenv.2014.05.070**

Golestan Province Meteorological Office, (2016). *http://portal.golestanmet.ir/*

Gollany, H.T., Novak, J.M., Liang, Y., Albrecht, S.L., Rickman, R.W., Follett, R.F., Wilhelm, W.W. & Hunt, P.G. (2010). Simulating soil organic carbon dynamics with residue removal using the CQESTR model. *Soil Science Society of America Journal*, *74*, 372–383. **doi: 10.2136/sssaj2009.0086**

Gottschalk, P., Smith, J.U., Wattenbach, M., Bellarby, J., Stehfest, E., Arnell, N., Osborn, T.J., Jones, C. & Smith, P. (2012). How will organic carbon stocks in mineral soils evolve under future climate?: Global projections using RothC for a range of climate change scenarios. *Biogeosciences*, *9*, 3151-3171. **doi: 10.5194/bg-9-3151-2012**

Grant, R.F., Arkebauer, T.J., Dobermann, A., Hubbard, K.G., Schimelfenig, T.T., Suyker, A.E., Verma, S.B. & Walters, D.T. (2007). Net biome productivity of irrigated and rainfed maize-soybean rotations: modeling vs. measurements. *Agronomy Journal*, *99*, 1404–1423. **doi: 10.2134/agronj2006.0308**

Han, B., Wang, X.K. & Ouyang, Z.Y. (2005). Saturation levels and carbon sequestration potentials of soil carbon pools in farmland ecosystems of China. *Rural Eco-Environment*, *21*, 6-11. [In Chinese]

Hua-jun, T., Jian-jun, Q., Li-gang, W., Hu, L., Chang-sheng, L. & Van Ranst, E. (2010). Modeling Soil Organic Carbon Storage and Its Dynamics in Croplands of China. *Agricultural Sciences in China*, *9*(5), 704-712. **doi: 10.1016/S1671-2927(09)60146-2**

Jin, L., Li, Y. E., Gao, Q. Z., Wan, Y. F. & Qin, X. B. (2010). Analysis of the change of soil carbon under cropland management in China between 1981 and 2000 by DNDC. *Chinese Journal of Soil Science*, *41*, 1081–1085. [In Chinese]

Lal, R., (2001). World cropland soils as a source or sink for atmospheric carbon. *Advanced Agronomy*, *71*, 145–191. **doi: 10.1016/s0065-2113(01)71014-0**

Lal, R. (2003). Global potential of soil carbon sequestration to mitigate the greenhouse effect. *Plant Sciences*, *22*, 151-184. **doi: 10.1080/713610854**

Lal, R. (2004). Soil carbon sequestration to mitigate climate change. *Geoderma*, *123*, 1–22. **doi: 10.1016/j.geoderma.2004.01.032**

Lal, R. & Bruce, J.P. (1999). The potential of world cropland soils to sequester C and mitigate the greenhouse effect. *Environmental Science and Policy*, *2*, 177–185. **doi: 10.1016/s1462-9011(99)00012-x**

Lemma, B., Kleja, D.B., Nilsson, I., Olsson, M. (2006). Soil carbon sequestration under different exotic tree species in the southwestern highlands of Ethiopia. *Geoderma*, *136*, 886-898. **doi: 10.1016/j.geoderma.2006.06.008**

Lenka N K, Lal R. (2013). Soil aggregation and greenhouse gas flux after 15 years of wheat straw and fertilizer management in a no-till system. *Soil and Tillage Research*, *126*, 78–89. **doi: 10.1016/j.still.2012.08.011**

Li, C. (2000). Modeling trace gas emissions from agricultural ecosystem. *Nutrient Cycling Agroecosystems*, *58*, 259–276. **doi: 10.1023/a:1009859006242**

Li, C., Frolking, S. & Frolking, T.A. (1992). A model of nitrous oxide evolution from soil driven by rainfall events: 1. Model structure and sensitivity. *Journal of Geophysical Research*, *97* (D9), 9759–9776. **doi: 10.1029/92jd00509**

Li, C., Frolking, S. & Harriss, R.C. (1994). Modeling carbon biogeochemistry in agricultural soils. *Global Biogeochemical Cycles*, *8*, 237-254. **doi:10.1029/94gb00767**

Li, C.S. (2001). Biogeochemical concepts and methodologies: Development of the DNDC model. *Quaternary Sciences*, *21*, 89–99. [In Chinese]

Li, C.S. (2007). Quantifying greenhouse gas emissions from soils: Scientific basis and modeling approach. *Soil Science and Plant Nutrition*, *53*, 344–352. **doi: 10.1111/j.1747-0765.2007.00133.x**

Li, C.S., Frolking, S., Crocker, G.J., Grace, P.R., Klir, J., Korchens, M. & Poulton, P.R. (1997). Simulating trends in soil organic carbon in long-term experiments using the DNDC model. *Geoderma*, *81*, 45–60. **doi: 10.1016/s0016-7061(97)00080-3**

Li, S., Li, Y., Li, X., Tian, X., Zhao, A., Wang, S., Wang, S. & Shi, J. (2016). Effect of straw management on carbon sequestration and grain production in a maize-wheat cropping system in Anthrosol of the Guanzhong Plain. *Soil and Tillage Research*, *157*, 43-51. **doi: 10.1016/j.still.2015.11.002**

Lokupitiya, E., Denning, S., Paustian, K., Baker, I., Schaefer, K., Verma, S., Meyers, T., Bernacchi, C.J., Suyker, A. & Fischer, M. (2009). Incorporation of crop phenology in Simple Biosphere Model (SiBcrop) to improve land-atmosphere carbon exchanges from croplands. *Biogeosciences*, *6*, 969–986. **doi: 10.5194/bg-6-969-2009**

Lugato, E., Berti, A. & Giardini L. (2006). Soil organic carbon (SOC) dynamics with and without residue incorporation in relation to different nitrogen fertilization rates. *Geoderma*, *135*, 315–321. **doi: 10.1016/j.geoderma.2006.01.012**

Luo, Z.K., Wang, E. & Sun, O.J. (2010). Soil carbon change and its responses to agricultural practices in Australian agro-ecosystems: a review and synthesis. *Geoderma*, *155*, 211-223. **doi: 10.1016/j.geoderma.2009.12.012**

Mishra, U., Lal, R., Liu, D. & Van Meirvenne, M. (2010). Predicting the spatial variation of the soil organic carbon pool at a regional scale. *Soil Science Society of America Journal*, *74*, 906–914. **doi: 10.2136/sssaj2009.0158**

Mosier, A.R., Halvorson, A.D., Reule, C.A. & Liu, X.J. (2006). Net global warming potential and greenhouse gas intensity in irrigated cropping systems in northeastern Colorado. *Journal of Environmental Quality*, *35*, 1584–1598. **doi: 10. 2134/jeq2005.0232**

Nelson, D.W. & Sommers, L.E. (1996). Total carbon, organic carbon, and organic matter. In: Sparks, D.L. (Ed.), Methods of Soil Analysis Part 3: Chemical Methods, SSSA Book Ser. 5. Soil Science Society of America, Madison, WI, pp: 961–1010.

NOAA, National Oceanic and Atmospheric Administration Website. *http://www.noaa.gov*

Pathak, H., Li, C.S. & Wassmann, R. (2005). Greenhouse gas emissions from Indian rice fields: calibration and up scaling using the DNDC model. *Biogeosciences*, *2*, 113–123. **doi: 10.5194/bg-2-113-2005**

Paul, K.I., Polglase, P.J., Nyakuengama, J.G. & Khann, P.K. (2002). Change in soil carbon following a forestation. *Forest Ecology Management*, *168*, 241–257. **doi: 10.1016/s0378-1127(01)00740-x**

Schlesinger, W.H. (1984). Soil organic matter: a source of atmospheric CO2. In: Woodwell, G.M. (Ed.), The Role Terrestrial Vegetation in the Global Carbon Cycle: Measurement by Remote Sensing. John Wiley & Sons Ltd., Chichester, pp: 111–127.

Smith, P., (2004a). Carbon sequestration in croplands: the potential in Europe and the global context. European *Journal of Agronomy*, *20*, 229–236. **doi: 10.1016/j.eja.2003.08.002**

Smith, P. (2004b). Soils as carbon sinks: the global context. *Soil Use Management*, *20*, 212–218. **doi: 10.1111/j.1475-2743.2004.tb00361.x**

Smith, J. & Smith, P. (2007). Environmental modelling: an introduction. Oxford University Press New York, USA.

Tang, H.J., Qiu, J.J., Van Ranst, E. & Li, C.S. (2006). Estimations of soil organic carbon storage in cropland of China based on DNDC model. *Geoderma*, *134*, 200–206. **doi: 10.1016/j.geoderma.2005.10.005**

Tonitto, C., David, M.B., Drinkwater, L.E. & Li, C.S. (2007). Application of the DNDC model to tile-drained Illinois agroecosystems: model calibration, validation, and uncertainty analysis. *Nutrient Cycling in Agroecosystems*, *78*, 51–63. **doi: 10.1007/s10705-006-9076-0**

Walkley, A. & Black, I.A. (1934). Na examination of the Degtjareff method for determiningsoil organic matter and a proposed modification of the chromic acid titration method. *Soil Science*, *37*, 29–38. **doi: 10.1097/00010694-193401000-00003**

Wallach, D., Makowski, D., Jones, J.W. & Brun, F. (2014). Working with Dynamic Crop Models: Methods, Tools and Examples for Agriculture and Environment. Elsevier Science, Academic Press, London, UK and MA, USA.

Wang, G.C., Huang, Y., Wang, E., Yu, Y.Q. & Zhang, W. (2013). Modeling soil organic carbon change across Australian wheat growing areas, 1960–2010. *Plos One*, *8*, e63324. **doi: 10.1371/journal.pone.0063324**

Webster, R. & Oliver, M. A. (2000). Geostatistics for environmental scientists. Wiley Press, 271p.

Xu, S., Shi, X., Zhao, Y., Yu, D., Wang, S., Tan, M., Sun, W. & Li, C. (2012). Spatially explicit simulation of soil organic carbon dynamics in China's paddy soils. *Catena*, *92*, 113-121. **doi: 10.1016/j.catena.2011.12.005**

Xu, S., Zhao, Y., Shi, X., Yu, D., Li, C., Wang, S., Tan, M. & Sun, W. (2013). Map scale effects of soil databases on modeling organic carbon dynamics for paddy soils of China. *Catena*, *104*, 67-76. **doi: 10.1016/j.catena.2012.10.017**

Yan, L., Wen-Liang, W., Fan Qiao, M. & Hu, L. (2016). Impact of agricultural intensification on soil organic carbon: A study using DNDC in Huantai County, Shandong Province, China. *Journal of Integrative Agriculture*, *15* (6), 1364-1375. **doi: 10.1016/s2095-3119(15)61269-2**

Zhang, W., Yu, Y.Q., Sun, W.J. & Huang, Y. (2007). Simulation of soil organic carbon dynamics in Chinese rice paddies from 1980 to 2000. *Pedosphere*, *17*, 1–10. **doi: 10.1016/s1002-0160(07)60001-0**

Zhang, P., Wei, T., Li, Y., Wang, K., Jia, Z., Han, Q. & Ren, X. (2015). Effects of straw incorporation on the stratification of the soil organic C, total N and C: N ratio in a semiarid region of China. *Soil Tillage Research*, *153*, 28–35. **doi: 10.1016/j.still.2015.04.008**

Zhang, L., Zhuang, Q., Li, X., Zhao, Q., Yu, D., Liu, Y., Shi, X., Xing, S. & Wang, G. (2016). Carbon sequestration in the uplands of Eastern China: An analysis with high-resolution model simulations. *Soil and Tillage Research*, *158*, 165-176. **doi: 10.1016/j.still.2016.01.001**