Chapter 3
Climate Change and Process-Based Soil Modeling

Mukhtar Ahmed, Sajid Ali, Adnan Zahid, Shakeel Ahmad, Nasim Ahmad Yasin, and Rifat Hayat

Abstract Soil is under pressure due to climate change. Higher temperature is increasing decomposition and mineralization of the soil organic matter (SOM), thus reducing soil organic carbon, which is the blood of the soil. Furthermore, rise in temperature is causing changes in soil moisture. In addition, elevated concentration of carbon dioxide (CO_2) could cause higher activity of soil microbes, thus breaking SOM at a faster rate and releasing more CO_2. Similarly, the production of methane (CH_4) will be more in future if current traditional agricultural practices would be carried out at the same pace. Thus, it is clear that warming is a responsible factor of higher greenhouse gas (GHGs) emissions from soil. Hence, in this chapter, we are proposing different techniques, which could be used to keep the carbon underground, thus making soil as sink, not the source. Carbon (C) sequestration is low-hanging fruit nowadays, being used to improve SOM. However, understanding or quantification of soil health is important to design adaptation and mitigation strategies to climate change. Modern day tools, such as remote sensing and modeling, can be used to quantify the health status of soil, as mentioned in this chapter. Similarly, knowledge of soil physical processes (e.g., hydrologic dynamics, energy dynamics, and overwinter dynamics) is utmost important to get good returns from the soil. Thus, the Green-Ampt approach, Darcy law, and moving multifront (MMF)

M. Ahmed (✉)
Department of Agronomy, PMAS Arid Agriculture University, Rawalpindi, Pakistan
e-mail: ahmadmukhtar@uaar.edu.pk

S. Ali · A. Zahid
Department of Agronomy, Faculty of Agricultural Sciences, Quaid-e-Azam Campus, University of the Punjab, Lahore, Pakistan

S. Ahmad
Department of Agronomy, Bahauddin Zakariya University, Multan, Pakistan

N. A. Yasin
SSG, RO-II Department, University of the Punjab, Lahore, Pakistan

R. Hayat
Institute of Soil and Environmental Sciences, Pir Mehr Ali Shah Arid Agriculture University, Rawalpindi, Pakistan

M. Ahmed (ed.), *Global Agricultural Production: Resilience to Climate Change*,
https://doi.org/10.1007/978-3-031-14973-3_3

were discussed in this chapter. Similarly, the approaches used by the different process-based models in their soil modules were elaborated. At the end of this chapter, the practical application of remote sensing and modeling was given at different spatiotemporal scale. Finally, it can be concluded that multiple adaptation and mitigation strategies should be used to improve SOM, which can further help to achieve sustainable development goals (SDGs), the blueprint to achieve a sustainable future for all.

Keywords SoilClimate change · Soil organic matter · Greenhouse gasses · Adaptation and mitigation · Remote sensing · Modeling

3.1 Soils and Climate Change

Soil is the loose surface material that covers the land, and it is the basic resource needed for the survival of living organisms. It contains organic and inorganic material. It is a living treasurer under our feet. Soil is a mixture of mineral matter, water, air, and organic matter as shown in Fig. 3.1. It is the natural medium which nourishes and supports plants. Soil is the end product of decomposition of the parent material. This weathering of the parent material is dependent upon climate, topography, and organisms like flora, fauna, and human. Hence, soil differs in texture, structure, color, physical, chemical, and biological properties. Soil is an important component of land and ecosystems, and it also determines the social and economic conditions of the region. Soil is the second largest store or sink of carbon after ocean, and to mitigate climate change, it is essential to improve soil organic matter (SOM) through different land management's techniques. The relationship between soil and climate change has been well described by the European Environmental Agency (Fig. 3.2). Similarly, soil management can play an important role in climate change adaptation and mitigation (Fig. 3.3). Improving carbon (C) in soil will help to protect

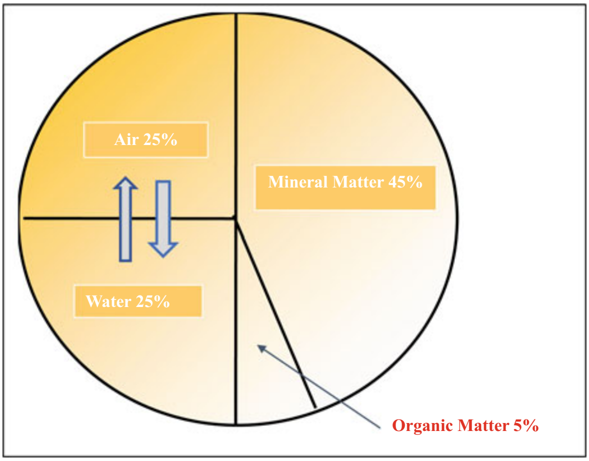


Fig. 3.1 Composition by volume of soil

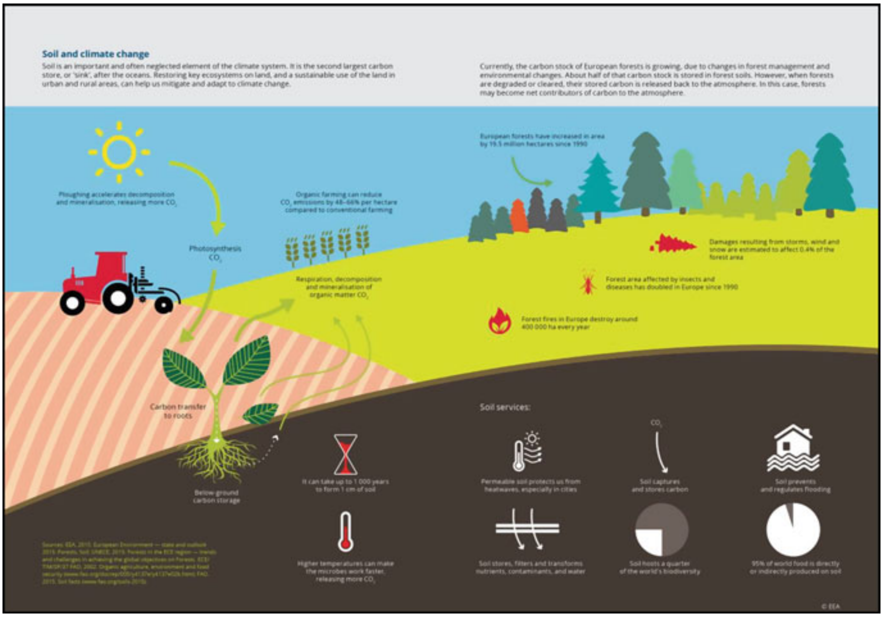


Fig. 3.2 Soil and climate change. (Source: European Environmental Agency (EEA))

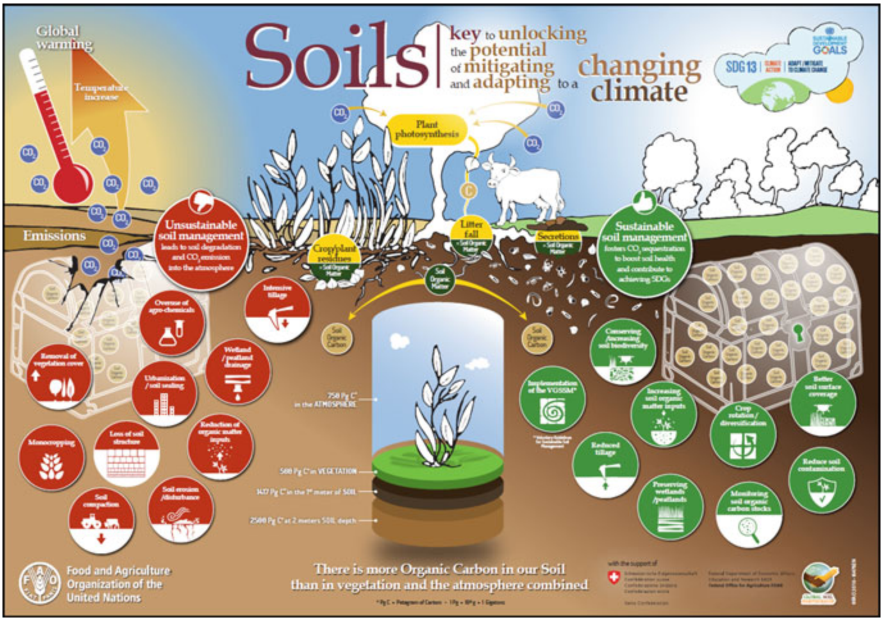


Fig. 3.3 Unlocking potentials of soil to mitigate and adapt to climate change. (Source: FAO)

soil from degradation, increases water holding capacity (WHC) of the soil, promotes microbial growth, and ensures food security. C-sequestration is the transfer of atmospheric CO_2 into different global pools (e.g., oceanic/pedologic/biotic and geological strata) to reduce the increase of CO_2 in the atmosphere. It is a very important technique which can help to maintain the concentration of carbon dioxide (CO_2) in the atmosphere, as concentration of CO_2 is increasing at a rapid pace. It has been increased from 280 ppm (1850) to 417 ppm (2022). This higher CO_2 concentration resulted to the increased surface temperature (1.5–5.8 °C) (IPCC 2001, 2014). C-sequestration have two basic methods, i.e., (i) direct (immediate binding at the source) and (ii) indirect (fixation of CO_2 by photosynthesis or its binding in a soil environment). Agriculture can play a significant role in C-sequestration. It is possible through agroforestry, soil mulching, residue incorporation, application of biochar, proper fertilization, intercropping, crop rotation, and growing of cover crops, which can further improve soil health by preventing soil degradation. Mattila et al. (2022) conducted a farmer participatory research to explore how farmers consider carbon (C) sequestration (low-hanging fruit). Farmers were given training about the basics of C-farming and C-farming plans to improve C-stocks in the field. The study suggested the use of remote sensing, modeling, and soil sampling as an integrated approach to verify the C storage in the field (Diaz-Gonzalez et al. 2022). C-sequestration is an important climate change mitigation approach. Therefore, C-farming was promoted to reduce climate change impact (Paustian et al. 2019). Lal (2008) suggested that reduction in atmospheric CO_2 loading is possible through biological, chemical, and technological options. Biological pumping, a C-sequestration technique in which CO_2 is injected below the ground surface to form carbonates, has so many benefits, which can enhance ecosystem services (e.g., improving soil quality and health, enhancing biodiversity, improving ground water quality, and increasing use efficiency of agronomic inputs), and ensures food security. Furthermore, C-sequestration reduces greenhouse effect (Kowalska et al. 2020; Lal 2005, 2008). Amundson and Biardeau (2018) reported that annual increase in atmospheric CO_2 can be halted if soil carbon could be increased by 0.4% on a yearly basis. Hence, soil C- sequestration is an important mitigation tool. Paustian et al. (2019) reported C-sequestration as an effective CO_2 removal strategy. Different management practices as elaborated in Table 3.1 could be opted to minimize the impact of climate change from soil.

3.2 Understanding Soil

Understanding of soil is very important to design adaptation and mitigation strategies to climate change as mentioned above. Knowledge of soil physical processes is utmost important to get good returns from soil. Soil physical processes include (i) hydrologic dynamics (infiltration, runoff, macropore flow, chemical transport, water table and tile flow, redistribution), (ii) energy dynamics (potential evapotranspiration, soil heat transport and temperatures, energy balance), and (iii) overwinter

Table 3.1 Management practices to increase soil C-sequestration and CO_2 removals

S. No	Management practices	Benefits	References
1.	Crop rotations and cover cropping	Higher C-sequester and economic returns Mitigating climate change Improvement in the soil quality Decrease CO_2 emission Improvement in soil temperature, moisture, and total aboveground biomass Reduces erosion and nitrogen leaching, fix atmospheric nitrogen and improves soil health Mitigation of CO_2 emissions	Chahal et al. (2020), Smith et al. (2008), Abdollahi and Munkholm (2014), Nguyen and Kravchenko (2021), Kaye and Quemada (2017) and Rigon and Calonego (2020)
2.	Composting	Reduces emissions of greenhouse gases (GHGs)	Favoino and Hogg (2008)
3.	Manuring	Reduction in GHGs emissions	Dalgaard et al. (2011)
4.	No tillage, zero tillage	Mitigate GHG emissions Viable greenhouse gas mitigation strategy Lower GHGs fluxes Application of DAYCENT model in the estimation of GHGs Minimizing emissions of GHGs Preservation of soil organic carbon	Ogle et al. (2019), Krauss et al. (2017), Forte et al. (2017), Rafique et al. (2014), Mangalassery et al. (2014) and Haddaway et al. (2017)
5.	Cultivation of perennial grasses and legumes	Higher soil C storage Reduced N_2O emissions Suppress weed invasion Reduced use of inorganic fertilizer Lowering of C-footprint	Yang et al. (2019), Liu et al. (2016) and Gan et al. (2014)
6.	Plantation of deep-rooted crops	Improved soil carbon budget Reduced emissions of CO_2 Improves soil structure Improves water and nutrient retention	Jansson et al. (2021) and Kell (2011)
7.	Rewetting organic soils	Lowering CO_2 and N_2O emissions	Wilson et al. (2016) and Paustian et al. (2016)
8.	Grazing land management	Lowers atmospheric CO_2 emissions and surface temperature Improvement of soil carbon stocks	Mayer et al. (2018) and Conant et al. (2017)
9.	Biochar application	Reduced N_2O emissions Improved soil water holding capacity Suppression of soil CO_2 emissions Variable response in CO_2 production Soil greenhouse gas (GHG) fluxes remained variable in response to different biochar application	Martin et al. (2015), Conant et al. (2017), Spokas and Reicosky (2009) and He et al. (2017)
10.	Plant-soil interactions	Restoration of degraded soil	Maiti and Ghosh (2020)

dynamics (simplistic snow accumulation and melt process). Infiltration of water into a layered soil could be monitored by the Green-Ampt approach, which requires saturated hydraulic conductivity K_S and wetting-front suction S_{WF} of each soil layer (Green and Ampt 1911). It is a mechanistic model for infiltration under ponded conditions with well-defined wetting front. The following equation elaborates parameters in the Green-Ampt infiltration model:

$$V = \overline{K}_S \frac{(S_{\mathrm{wf}} + H_O + Z_{\mathrm{WF}})}{Z_{\mathrm{WF}}}$$

where S_{WF} = integral of relative unsaturated hydraulic conductivity $K(h)/K_s$, known or derived from soil-water retention curve, $\theta(h)$ and θ = volumetric soil water content, and h = soil-water pressure head ($-$ive soil-water suction). Due to air entrapment, field-saturated θ_s is about 0.90 and effective K_s is approximately $K_s/2$. Further description about Green-Ampt infiltration model has been shown in Fig. 3.4.

Water penetration from the ground into the soil is governed by the soil surface condition, vegetation cover, soil properties, hydraulic conductivity, and antecedent

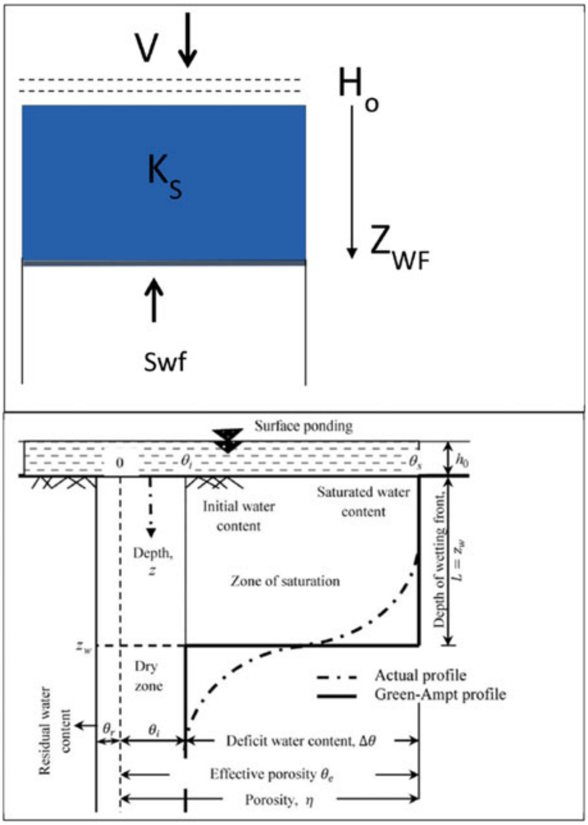


Fig. 3.4 Green-Ampt infiltration model. (Source: Kale and Sahoo 2011)

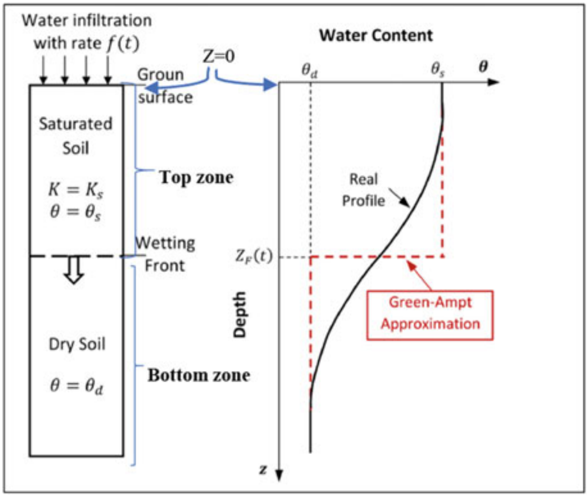


Fig. 3.5 Green-Ampt piston flow. (Source with permission via Rightslink: Alastal and Ababou 2019)

soil moisture. Generally, it has four zones (i) saturated, (ii) transmission, (iii) wetting, and (iv) wetting front. The rate at which water enters the soil is called infiltration rate, represented as f(t), while cumulative infiltration ($F(t)$) is the accumulated depth of water infiltrating during given time period. The Green-Ampt infiltration model (GAIM) assumes saturated piston-type flow into the dry soil (flow is modeled as the displacement of a single sharp wetting front into a dry soil). The front sharply separates in two regions, i.e., (i) fully saturated region (above) and (ii) very dry region (Below). The wetting front move downward due to gravity and capillary suction (Fig. 3.5). The GAIM is a single front model as it is based on the movement of a single front (Zf(t)) as shown in Fig. 3.5. The GAIM divides the soil into two zones as shown in Fig. 3.5.

Darcy law could be used to describes water flux (q). For example, in case of two-layered soil as shown in Fig. 3.6, water flux for the first layer (q_1) and second layer could be monitored by the following equations:

$$\text{Water flux for the 1st layer}(q_1)\ (\text{Volume per unit area per unit time})$$

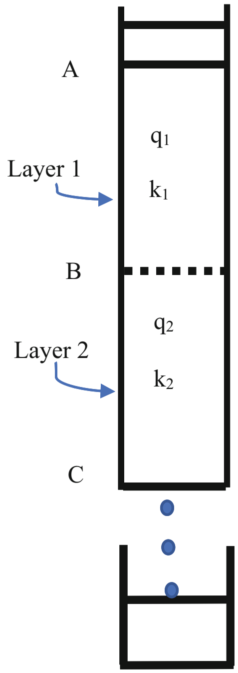
$$= \text{Hydraulic conductivity of 1st layer } (K_1) \times \frac{\text{Hydraulic gradient}(\Delta H_1)}{L_1\ (\text{Thickness of 1st layer})}$$

$$= K_1 \frac{H_A - H_B}{L_1}$$

$$\therefore \frac{q_1 L_1}{K_1} - H_A = -H_B$$

$$\therefore -\frac{q_1 L_1}{K_1} + H_A = H_B$$

Fig. 3.6 Darcy law for layered soils



$$H_B = H_A - \frac{q_1 L_1}{K_1}$$

Water flux for the 2nd layer(q_2) (Volume per unit area per unit time)

$$= \text{Hydraulic conductivity of 1st layer } (K_2) \times \frac{\text{Hydraulic gradient}(\Delta H_2)}{L_2 \text{ (Thickness of 2nd layer)}}$$

$$= K_2 \frac{H_B - H_C}{L_2}$$

$$\therefore q_2 = \frac{K_2}{L_2} (H_B - H_c)$$

Putting the value of H_B from the first layer into second-layered equation generates the following equation:

$$q_2 = \frac{K_2}{L_2} \left(H_A - \frac{q_1 L_1}{K_1} - H_c \right)$$

For a steady state system, flux will be:

$$q_1 = q_2 = q$$

Hence,

$$q = \frac{K_2}{L_2}\left(H_A - \frac{qL_1}{K_1} - H_c\right)$$

After rearrangement, equation will be:

$$\frac{qL_2}{K_2} + \frac{qL_1}{K_1} = H_A - H_C$$

$$q\left(\frac{L_2}{K_2} + \frac{L_1}{K_1}\right) = H_A - H_C$$

Hence, Dracy's law for layered soil will be:

$$q = \frac{H_A - H_C}{\frac{L_2}{K_2} + \frac{L_1}{K_1}}$$

Let $\frac{L\ \text{(lenght of the given soil layer)}}{K\ \text{(Hysraulic conductivity of the soil layer)}} = \text{Hydraulic resistanc}e = R_h$
Then

$$q = \frac{H_A - H_C}{R_{h_1} + R_{h_2}} = \frac{\Delta H}{R_{h_1} + R_{h_2}} =$$

Alastal and Ababou (2019) developed and tested moving multifront (MMF) to solve the Richards equation (Fig. 3.7). The root uptake part of the sink term $W(z,t)$ could be evaluated by using the approach of Nimah and Hanks (1973). Evapotranspiration is generally monitored by using the Penman-Montieth or Shuttleworth and Wallace methods.

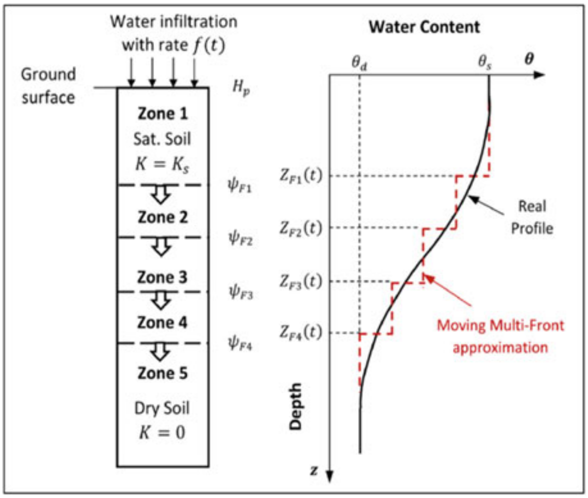


Fig. 3.7 Moving multifront (MMF) model. (Source with permission via Rightslink: Alastal and Ababou 2019)

3.3 Soil Modules in Different Models

3.3.1 AquaCrop

AquaCrop is a FAO model, and it uses soil water balance, soil water movement, and soil profile characteristic modules. The functioning of soil water module in AquaCrop is elaborated in Fig. 3.8. AquaCrop derives soil texture, organic matter, soil compaction, and stoniness by using hydraulic properties calculator developed by the USDA and Washington State University (https://hrsl.ba.ars.usda.gov/soilwater/Index.htm).

3.3.2 Agricultural Production Systems sIMulator (APSIM)_Soil Module

The APSIM is an internationally well-known model (https://www.apsim.info/). The APSIM soil module has multiple components, i.e., (i) erosion, (ii) fertilizer, (iii)

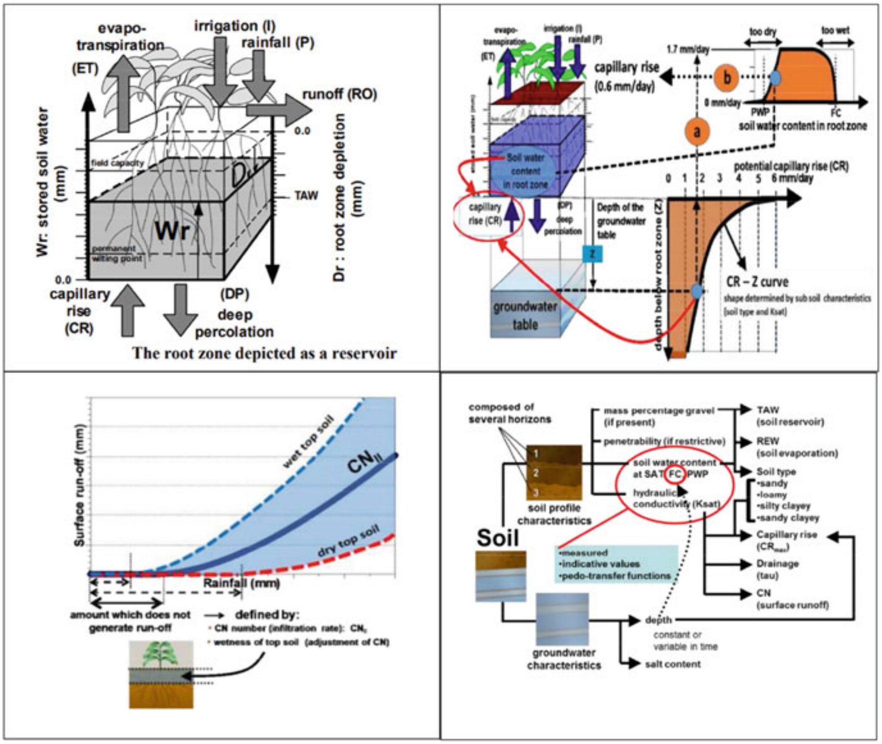


Fig. 3.8 Description of soil module in AquaCrop

irrigation, (iv) map, (v) SoilN, (vi) SoilP, (vii), SoilTemp, (viii), SoilWat (ix), solute, (x) surface, (xi) SurfaceOM, (xii) SWIM, (xiii) SWIM3, and (xiv) WaterSuppl. The APSIM soil module is diagrammatically presented in Fig. 3.9. Both C and N dynamics has been described by SoilN module as elaborated in Fig. 3.10, where

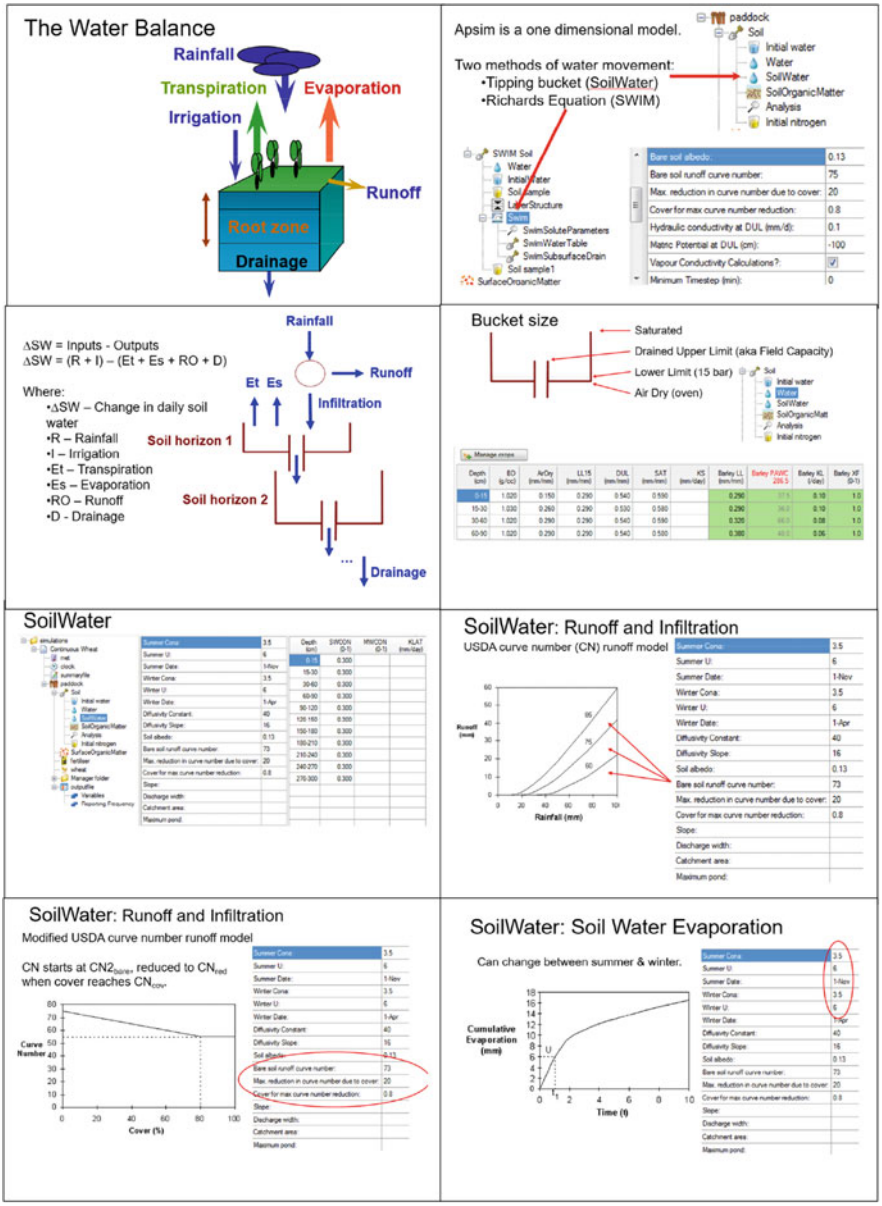


Fig. 3.9 Diagrammatic representation of the APSIM soil module. (Source: APSIM)

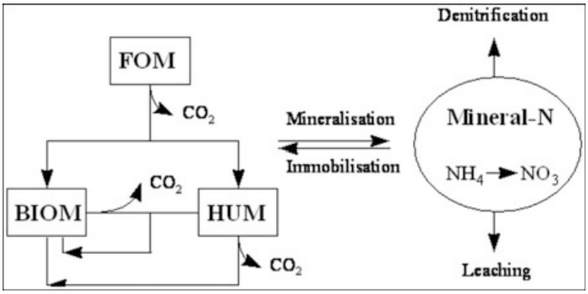


Fig. 3.10 Transformation in the APSIM_soilN module. (Source: APSIM)

SOM is divided into two pools (Hum and Biom). Labile, soil microbial biomass, and microbial products are represented by "biom" pool, while the rest of the SOM comprises "hum." The flow between different pools is quantified in terms of C, while N flows depend upon C:N ratio of receiving pool. The "ini file" is used to specified C:N for "biom," while for "hum" it comes from the soil as an input. Decomposition in these two pools were calculated as first-order processes with a rate constant being modified by soil moisture and temperature in the layer. The CERES_Maize approach was used to represent fresh organic matter pool (fom), while C:N factor determines "fom" rate of decomposition (Jones 1986). Mineral N is determined though balance between decomposition and immobilization. At initialization, "hum" and "biom" C amount is calculated using soil inputs. The following equations will represent total, organic C, inert C, biom_C, and hum_C at initialization:

$$\text{Total C} = \text{Fresh organic matter (FOM) C} + \text{Orgnaic carbon (OC)}$$

$$\text{Organic Carbon}\left(\text{Kg ha}^{-1}\right) = \text{biom\_C} + \text{hum\_C}$$

$$\text{inert \_ C} = F_{\text{inert}} \times \text{OC}(\text{Kg ha}^{-1})$$

$$\text{biom\_C} = F_{\text{biom}} \times (\text{hum\_C} - \text{inert\_C})$$

since

$$\text{hum\_C} = \text{OC} - \text{biom\_C}$$

Thus, biom_C equation will be:

$$\text{biom\_C} = \frac{(F_{\text{biom}} \times (\text{OC} - \text{inert\_C}))}{(1 - F_{\text{biom}})}$$

$$\text{hum\_C} = \text{OC} - \text{biom\_C}$$

Soil temperature in the APSIM_Soil module is calculated using the Williams (1984) approach as applied in the EPIC (erosion-productivity impact calculator) model. The following equations were used in the EPIC model:

$$T(Z,t) = \overline{T} + \frac{\mathrm{AM}}{2}\exp\left(\frac{-Z}{\mathrm{DD}}\right)\cos\left(\frac{2\pi}{365}(t-200) - \frac{Z}{\mathrm{DD}}\right)$$

where Z = depth from the soil surface (mm), t = time (days), T = average annual air temperature (°C), AM = annual amplitude in daily average temperature (°C), and DD = damping depth for the soil (mm). However, this equation provides the same value for soil temperature as is for air temperature. Hence, to use air temperature as a driver for the soil temperature, the new equation developed was:

$$\mathrm{TG}_{\mathrm{IDA}} = (1-\mathrm{AB})\left(\frac{T_{\max} + T_{\min}}{2}\right)\left(1 - \frac{\mathrm{RA}}{800}\right) + T_{\max}\frac{\mathrm{RA}}{800} + (\mathrm{AB}) \times (\mathrm{TG}_{\mathrm{IDA}-1}) \ldots\ldots\ldots$$

where TG = soil surface temperature (oC), AB = surface albedo, T_{max} = maximum daily air temperature, T_{min} = minimum daily air temperature, and RA = daily solar radiation.

The final equation for calculating soil temperature at any depth is:

$$T(Z,t) = \overline{T} + \left(\frac{\mathrm{AM}}{2}\cos\left(\frac{2\pi}{365}(t-200) + \mathrm{TG} - T(O,\quad t)\right)\right)e^{-Z/\mathrm{DD}}$$

Decomposition of SOM pools in the APSIM_Soil module was calculated using the following equations:

$$\begin{aligned}\text{fom decomposition} = {} & F_{\text{pool}}(\text{Carbohydate, cellulose or lignin fraction}) \\ & \times \text{decay rate (rd)for a give fraction}\left(\text{rd}_{\text{carb}}, \text{rd}_{\text{cell}}, \text{rd}_{\text{lign}}\right) \\ & \times \text{Soil water factor} \times \text{Soil tempearture factor} \times \text{C} \\ & \text{: N factor}\end{aligned}$$

$$\begin{aligned}\text{biom decomposition} = {} & \text{biom} \times \text{rd}_{\text{biom}} \times \text{Soil water factor} \\ & \times \text{Soil temperature factor}\end{aligned}$$

$$\begin{aligned}\text{hum decomposition} = {} & (\text{hum} - \text{inert\_C}) \times \text{rd}_{\text{hum}} \times \text{Soil water factor} \\ & \times \text{Soil temperature factor}\end{aligned}$$

The factors affecting individual decay rates are shown in Fig. 3.11. Nitrification is an APSIM_Soil module which is calculated using the Michaelis-Menton kinetics. The following equations have been used to determine the nitrification rate:

$$\text{Potential rate} = \frac{\text{Nitrification}_{\text{pot}}(\text{mg N/kg soil/day}) \times \text{NH}_{4(\text{ppm})}}{\left(\text{NH}_{4(\text{ppm})} + \text{NH}_{4\text{ at half pot (ppm)}}\right)}$$

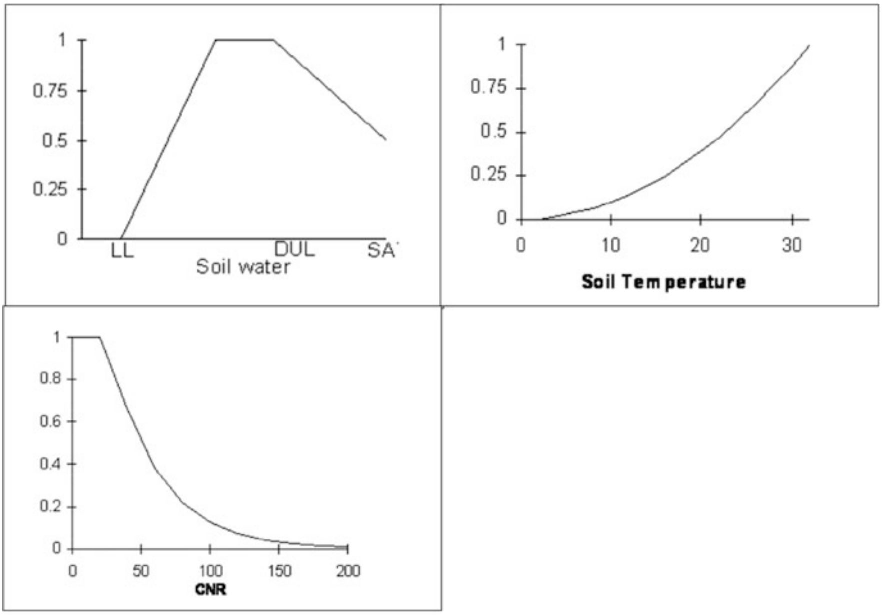


Fig. 3.11 Factors affecting SOM decay rates. (Source: APSIM)

$$\text{Nitrification rate} = \text{Potential rate} \times \min\left(\text{water factor, temperature factor, pH factor}\right)$$

Factors, i.e., soil water, temperature, and pH, affecting the nitrification rate of ammonium, are shown in Fig. 3.12. Nitrous oxide (N_2O) emission from nitrification is calculated using the following equation:

$$\mathrm{N_2O} = K2 \times R_{\mathrm{nit}}$$

where Rnit = rate of nitrification ((kg N ha^{-1} day^{-1}) and range of values as were used for $K2$ (Li 2000). Denitrification in APSIM_Soil module was taken from CERES-Maize V1, which uses the following equations:

$$\text{Denitrification rate} = 0.0006 \times \mathrm{NO_3} \times \text{Active C}_{\mathrm{ppm}} \times \text{water factor} \times \text{temperature factor}$$

where

$$\text{Active C}_{\mathrm{ppm}} = 0.0031 \times \left(\text{hum\_C}_{\mathrm{ppm}} + \text{FOM\_C}_{\mathrm{ppm}}\right) + 24.5$$

Factors affecting denitrification of nitrate is shown in Fig. 3.13. Further details of all other components in APSIM_Soil module are available on https://www.apsim.info/documentation/model-documentation/soil-modules-documentation/

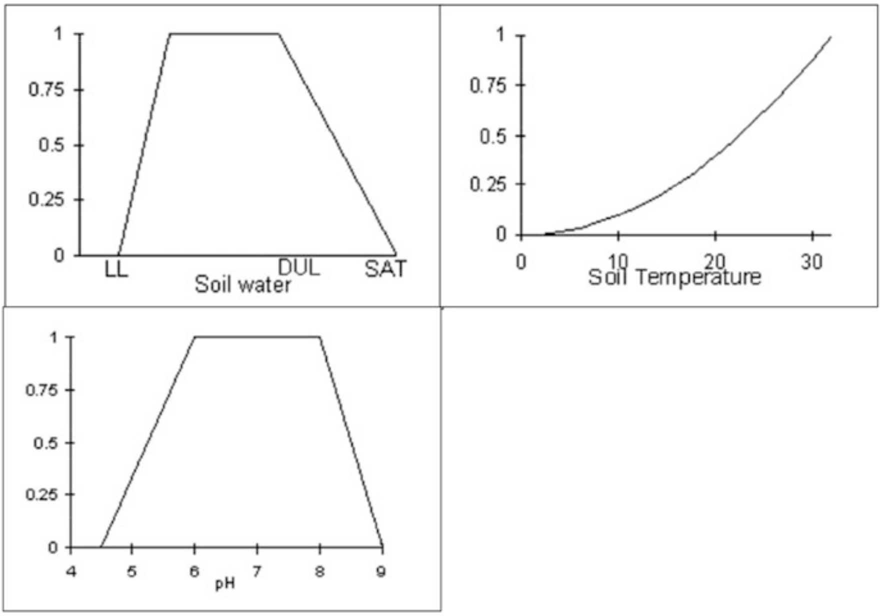


Fig. 3.12 Factors affecting *nitrification rate of ammonium.* (Source: APSIM)

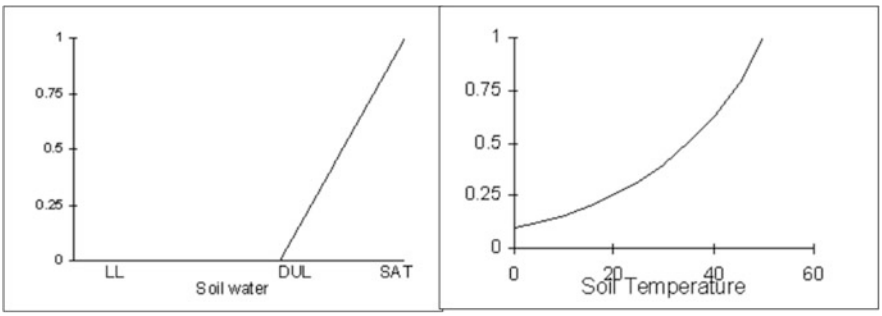


Fig. 3.13 Factors affecting *denitrification.* (Source: APSIM)

3.3.3 Decision Support System for Agrotechnology Transfer (DSSAT)_Soil Module

The simulation of the dynamics of soil in DSSAT is possible through different soil modules. These include soil water, inorganic soil N, soil P, and soil K modules. DSSAT also has soil organic matter modules with two options: (i) CERES-Godwin soil organic matter module and (ii) CENTURY (Parton) soil organic matter module. Furthermore, DSSAT has GHG emission modules, i.e., CERES denitrification, DayCent denitrification, N-gas emissions, and methane emissions. The DSSAT_soil module can also simulate dynamic soil properties as well as flood N dynamics. Further detail is available at https://dssat.net/models-overview/components/soil-module/

3.3.4 CropSyst_Soil

CropSyst simulates soil water budgets (precipitation, irrigation, runoff, interception, water infiltration, water redistribution in the soil profile), nutrients budgets (N and P), and C cycling on daily as well as hourly time step. Soil water fluxes in CropSyst is determined by a simple cascading approach or by a finite difference approach. Evapotranspiration in CropSyst can be calculated by three approaches, i.e., (i) Penman-Monteith model (ii) Priestley-Taylor model, and (iii) simpler implementation of the Priestley-Taylor, which considers only air temperature (Stöckle et al. 2003).

3.3.4.1 CropSyst Carbon/Nitrogen Model

This portion of the carbon/nitrogen model only includes the description of decay and mineralization of organic residues (crop, manure, etc.) incorporated into soil layers and dead roots. Surface residues are treated in a separate module using a slightly different approach. The pools included in the model are given in Table 3.2, all of them with units of kg m^{-2} ground area and with specified carbon/nitrogen ratios, except for residues whose ratio depends on their specific nitrogen content. The separate set of pools are defined for each soil layer. Figure 3.1 depicts the relations and exchanges of carbon (and nitrogen indirectly) among pools. Decomposition of organic residues and organic matter follows first-order kinetics with the following decomposition constants (day^{-1}).

A significant fraction of the carbon resulting from the decomposition of the different pools is lost as CO_2, and the rest is transferred to other pools (Fig. 3.14) according to the following carbon distribution fractions, where $F_{X\text{-}>Y}$ represents the fraction of carbon transferred from pool X to pool Y (Badini et al. 2007).

$$F_{R\rightarrow \mathrm{CO_2}} = 0.55$$

$$F_{R\rightarrow \mathrm{MB}} = 1 - F_{R\rightarrow \mathrm{CO_2}}$$

$$F_{\mathrm{MB}\rightarrow \mathrm{CO_2}} = \mathrm{Minimum}\left[(0.55),\left(0.85 - 0.68\left(F_{\mathrm{Silt}} + F_{clay}\right)\right)\right]$$

where F_{Silt} and F_{Clay} are the soil silt and clay fractions, respectively.

$$F_{\mathrm{MB}\rightarrow P} = 0.003 + 0.032\, F_{\mathrm{Clay}}$$

Table 3.2 Description of different pools in the CropSyst carbon/nitrogen model

Acronym	Description	Carbon/nitrogen ratio
R	Organic residue	Variable
MB	Microbial biomass	10
LA	Labile active soil organic matter	10
MA	Metastable active soil organic matter	10
P	Passive soil organic matter	10
Pool	**Notation**	**Value**
R	K_R	0.02
MB	K_{MB}	0.02 [1–0.75(F_{Silt}+F_{Clay})]
LA	K_{LA}	0.01
MA	K_{MA}	0.00055
P	K_P	0.000019

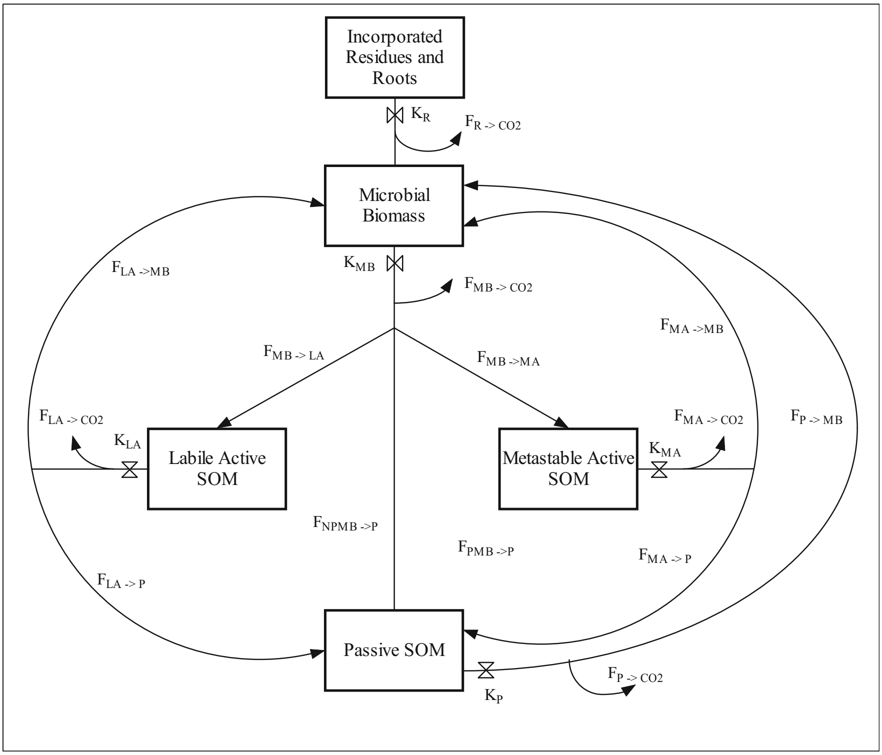


Fig. 3.14 CropSyst conceptual carbon flow model. (Source with permission: Badini et al. 2007)

$$F_{\mathrm{MB}\to\mathrm{LA}} = (1 - F_{\mathrm{MB}\to\mathrm{CO_2}} - F_{\mathrm{MB}\to P})\mathrm{FNPSV}$$

$$F_{\mathrm{MB}\to\mathrm{MA}} = (1 - F_{\mathrm{MB}\to\mathrm{CO_2}} - F_{\mathrm{MB}\to P})(1 - \mathrm{FNPSV})$$

where FNPSV is the fraction of non-protected soil volume, which is zero or low for consolidated and undisturbed soil layers and higher for layers recently disturbed by tillage.

$$F_{\mathrm{LA}\rightarrow\mathrm{CO_2}} = F_{\mathrm{MA}\rightarrow\mathrm{CO_2}} = F_{P\rightarrow\mathrm{CO_2}} = 0.55$$

$$F_{\mathrm{LA}\rightarrow P} = F_{\mathrm{MA}\rightarrow P} = \mathrm{Maximum}\left[(0.0),\ \left(0.003 - 0.009F_{\mathrm{Clay}}\right)\right]$$

$$F_{\mathrm{LA}\rightarrow\mathrm{MB}} = 1 - F_{\mathrm{LA}\rightarrow\mathrm{CO_2}} - F_{\mathrm{LA}\rightarrow P}$$

$$F_{\mathrm{MA}\rightarrow\mathrm{MB}} = 1 - F_{\mathrm{MA}\rightarrow\mathrm{CO_2}} - F_{\mathrm{MA}\rightarrow P}$$

$$F_{P\rightarrow\mathrm{MB}} = \left(1 - F_{P\rightarrow\mathrm{CO_2}}\right)$$

The carbon transferred among pools also determines the nitrogen transfer, which is equal to the amount of nitrogen required to preserve the carbon/nitrogen ratio of the receiving pools. In this process, if the amount of nitrogen released by the decomposing pool is greater than the amount of nitrogen required by the receiving pools, mineral nitrogen in the form of ammonium is released to the soil layer (mineralization). If the opposite is true, ammonium (first source) and nitrate (secondary source) from the soil layer is taken up for microbial consumption (immobilization). If no sufficient mineral nitrogen is available in the soil to supply the microbial demand, the decomposition is reduced in all pools requiring immobilization proportionally to the fraction of immobilization demand not satisfied. The initial amount of carbon allocated to each soil organic matter (SOM) pool in Fig. 3.14 depends on the organic matter content of the soil layer, expressed in kg carbon per square meter ground area. The total amount of carbon initially present in the soil layer is apportioned to each pool as mentioned in Table 3.3.

3.3.5 STTCS (Simulateur mulTIdisciplinaire Pour les Cultures Standard)

STICS is a model developed by INRA (France), now called as INRAE (Brisson et al. 2003). Soil surface can modify the water and heat balances in STICS, and it is linked

Table 3.3 Total amount of carbon in different pools

Pool	Fraction
Microbial biomass	0.02
Labile active SOM	(1 – Microbial biomass fraction – passive SOM fraction) physically non-protected soil volume
Metastable active SOM	(1 – Microbial biomass fraction – passive SOM fraction) physically protected soil volume
Passive SOM	Minimum (0.5, 0.3 + 0.4 F_{Clay}) for grasslands Minimum (0.5, 0.4 + 0.2 F_{Clay}) for croplands

Source: Badini et al. (2007)

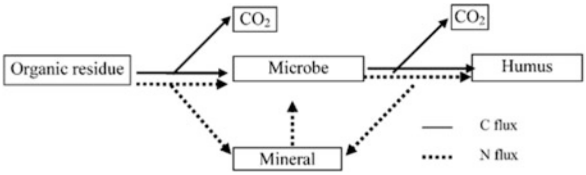


Fig. 3.15 C and N fluxes in STICS. (Source with permission: Brisson et al. 2003)

with the albedo of soil in dry state. Runoff coefficients determines the runoff proportion above a threshold in the presence of plants or mulch. Water balance in STICS is computed by using precipitation, irrigation, and reference evapotranspiration. Bulk density, field capacity, and wilting point was assumed constant in each soil horizon. The whole soil profile in STICS was characterized by five horizons of different depth. Beer's law is applied to calculate potential evaporation. N balance in STICS is calculated through N mineralization that originates from the three pools of organic matter (OM), i.e., (i) humified OM, (ii) microbial biomass (BIOM), and (iii) crop residues (RES) (Fig. 3.15). Denitrification (the gaseous loss) was calculated by using the NEMIS model (Hénault and Germon 2000). Nitrogen absorption is linked to crop requirements and supply from soil root system. Crop requirements was connected with the upper envelop of N dilution curves as reported by Lemaire and Gastal (1997). Soil N supply is equal to two fluxes, i.e. (i) transport flux (NO_3^{-1} transport via convection and diffusion from soil to closet root) and (ii) sink flux (active absorption by the root). In case of legumes, symbiotic fixation option is available that maintains N nutrition at the critical N level, and it depends on nodule activity, NO_3^{-1} presence, water stress, anoxia, and temperature. Soil temperature in STICS is calculated by using the model of McCann et al. (1991), which considers daily crop temperature and its amplitude (Brisson et al. 1998, 2003).

3.3.6 Erosion Productivity Impact Calculator (EPIC)

The EPIC model was developed by Williams (1984) to quantify the relationship between erosion and productivity. It is one of the comprehensive cropping system models developed initially (Williams et al. 1989; Williams 1990, 1995; Rosenberg et al. 1992; Stockle et al. 1992). The extended version of EPIC is APEX (Agricultural Policy/Environmental eXtender) developed by Texas A&M University (Jones et al. 2021; Gassman et al. 2009). Izaurralde et al. (2012) elaborated the development and application of EPIC in C-cycle, GHG mitigation. The EPIC model can simulate more than 100 crops, and it uses the Seligman and Keulen (1980) approach to calculate N transformations and dynamics. Afterward, soil organic carbon was calculated using a fixed fraction of soil organic N and C:N ratio of 10. This gives realistic picture of soil C dynamics and fluxes of C. However, EPIC performance to simulate long-term C dynamics was not up to mark as compared to other models, i.e., CENTURY, DNDC (DeNitrification DeComposition), ecosys, RothC, SOCRATES (Soil Organic Carbon Reserves And Transformations in agro-EcoSystems) used in

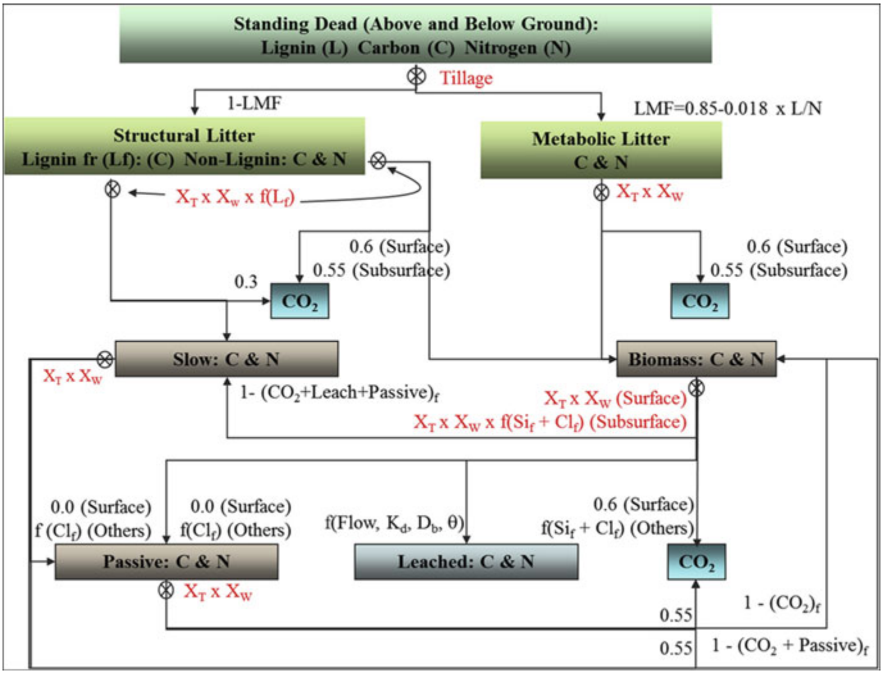


Fig. 3.16 EPIC soil C and N pools with their flows. (Source with permission: Jones et al. 2021)

the study conducted in Canada (Izaurralde et al. 2001). Hence, for improvement in EPIC, C-dynamics was needed, as elaborated by Jones et al. (2021). The C and N in SOM are distributed among the three pools as shown in Fig. 3.16 Furthermore, C balance in ecosystem prospective is given in Fig. 3.17, as EPIC generally gives C only in plant material, but with this modification, EPIC can describe C cycling at an ecosystem scale (Jones et al. 2021).

3.3.7 WOrld FOod Studies Crop Simulation Model (WOFOST)

WOFOST is a mechanistic, dynamic simulation model, which can simulate the production of annual crops (van Diepen et al. 1989; de Wit et al. 2019) in response to different managements and climate change. The WOFOST_Soil module includes soil water balance using tipping bucket and SWAP (soil-water-atmosphere-plant) approach. SWAP uses the Richards equation to simulate the flow of water and solutes among different layers (Kroes et al. 2009). WOFOST has also been connected through the BioMA framework to simulate soil water balance (Donatelli et al. 2010). WOFOST has the potential to be used in precision agriculture and smart farming.

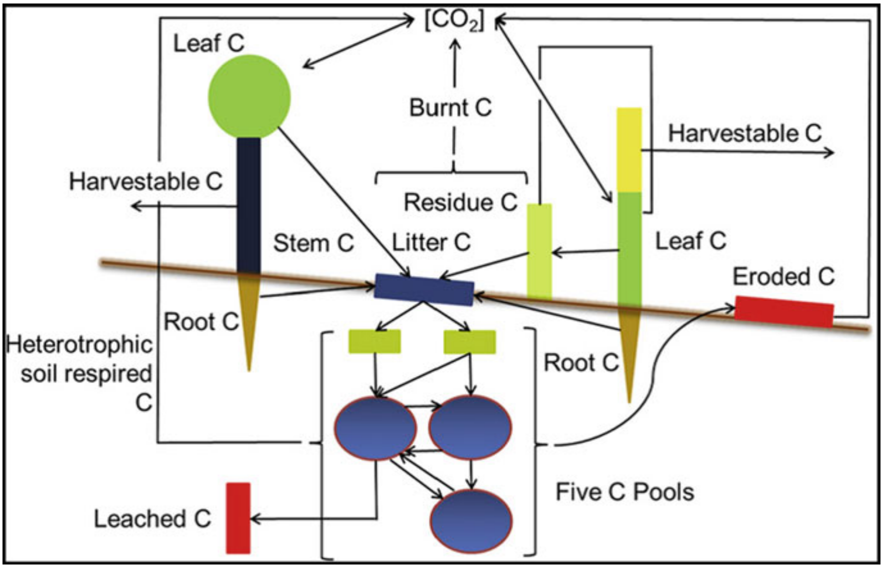


Fig. 3.17 EPIC ecosystem C balance. (Source with permission: Jones et al. 2021)

3.3.8 DNDC (DeNitrification DeComposition)

DNDC is a mathematical model that has been used in the study of management and climate change impacts on agriculture. DNDC has the potential to simulate dynamics (production, consumption, and transport) of nitrous oxide from different sources in agricultural systems (Gilhespy et al. 2014). Initially, DNDC (1–7) has three submodels, i.e., (i) denitrification (ii), decomposition (three soil organic carbon pools), and (iii) Soil_Climate_thermal hydraulic flux (Li et al. 1992). However, in DNDC_7.1, an additional empirical plant growth submodel was added; thus, it has four submodels. DNDC has so many further versions (e.g., PnET-N-DNDC, DNDC v. 8.0, Crop-DNDC, DNDC v. 8.2, Wetland-DNDC, UK-DNDC, DNDC v. 8.5, Forest-DNDC, NZ-DNDC, Forest-DNDC-Tropica, EFEM-DNDC, BE-DNDC, DNDC v. 9.0, DNDC-Europe, DNDC-Rice, and Mobile-DNDC), which was built to answer multiple questions of different scenarios. Smith et al. (2010) suggested improvement in the DNDCv9.3. estimation of soil evaporation. Manure-DNDC can quantify the manure life cycle on farms, and DNDCv.9.5 is the latest updated version, which can quantify hydrological features and GHGs estimation (Zhang and Niu 2016). Fluxes of GHGs among soil, plant, and atmosphere that elaborate DNDC mechanisms are shown in Fig. 3.18. Li et al. (2019) conducted a study to suggest improvement in the DNDC simulation of ammonia (NH_3) volatilization. They suggested major modifications in the source code. These include pedo-transfer functions in soil hydraulic parameters to simulate soil moisture, temperature effect on ammonium bicarbonate decomposition, and soil texture effect on NH_3 volatilization (Fig. 3.19).

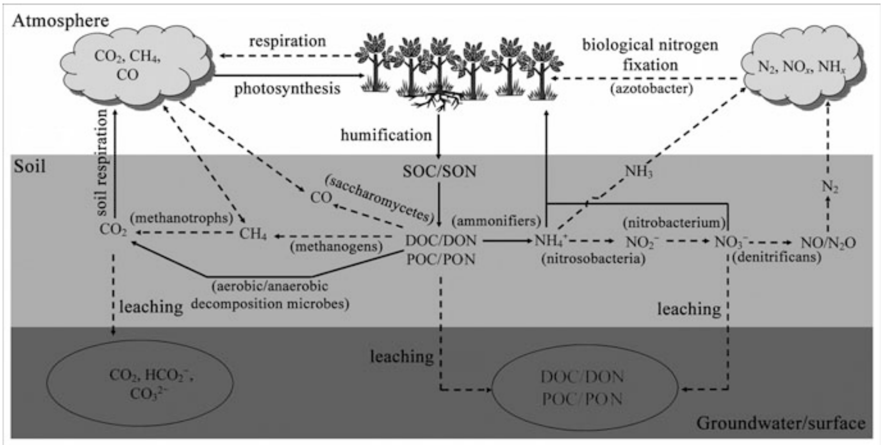


Fig. 3.18 Diagrammatic representation of DNDC showing carbon dioxide (CO_2), nitrous oxide (N_2O), and methane (CH_4) fluxes in forest/arable soil. (Source with permission: Zhang and Niu 2016)

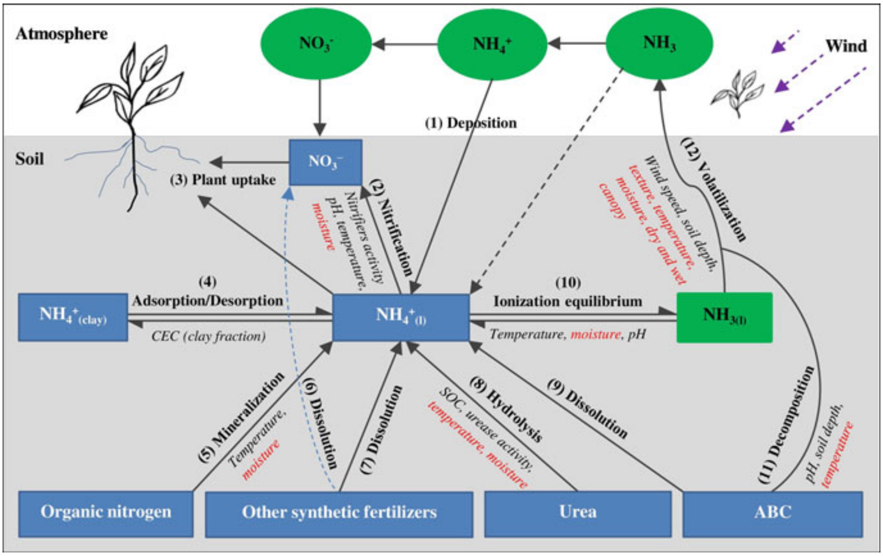


Fig. 3.19 Ammonia (NH_3) volatilization in DNDC. (Source with permission: Li et al. 2019)

3.4 Monitoring Soil Through Remote Sensing

Soil quality has been deteriorated due to intensive agriculture, and it poses big challenge to ensure food security. Traditional and modern soil quality assessment tools for data collection and processing can offer good opportunities to improve soil

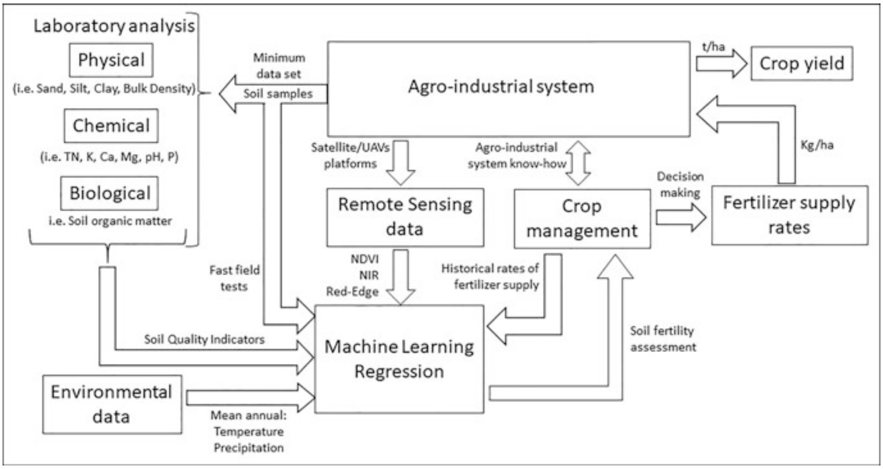


Fig. 3.20 Application of remote sensing and machine learning in soil quality assessments. (Source with permission: Diaz-Gonzalez et al. 2022)

health through different managements (Jung et al. 2021; Ge et al. 2011; Campbell et al. 2022; Bretreger et al. 2022; Angelopoulou et al. 2019). Artificial intelligence techniques provide useful information to farmers to decide treatments as per need. Generally, soil is assessed before the sowing of crop to select accurate management practices. But soil quality cannot be determined directly, and it can only be estimated by a wide range of quality indicators/indices. Traditional indicators to assess soil quality are (i) physical, (ii) chemical, and (iii) biological. Remote sensing is a powerful tool, which can be used to build different types of soil quality indicators based on soil nutrients and SOC contents (Fig. 3.20). However, to process data from remote sensing systems, different machine learning techniques are used. It includes supervised learning methods, i.e., random forest, support vector regression, artificial neural network, bagging decision tree, Bayesian models, boosted regression trees, cubist model, regression tree, regression kriging, random forest regression, partial least squares, k-nearest neighbor, generalized linear model, and deep learning (Diaz-Gonzalez et al. 2022; Harrington 2012; Loureiro et al. 2019; Bhatnagar and Gohain 2020).

3.5 Models Applications

Climate change is negatively affecting the crop productivity and food security due to its direct or indirect effect on different soil processes. Thus, adaptation options are needed to address the issue of climate change. The AquaCrop model was used by Alvar-Beltrán et al. (2021) to study the impact of climate change on the major crops (What and Sugarcane) of Pakistan, which is fifth in number due to the occurrence of extreme weather events. The study suggested that policy makers should act swiftly with solid adaptation options to cope with the changing environmental conditions in Pakistan. Bird et al. (2016) studied the relationship of future yield (2040–2070) variability with soil texture and climate models using AquaCrop to develop possible adaptation strategies. Results showed that yield was reduced by 64% on clay loams while it was increased by 8% on sandy loams and 26% on sandy clay loams soils. They suggested change in plant date and mulching as sustainable adaptation options to reduce crop losses. AquaCrop and DRAINMOD-S were used in a paddy field to simulate salt concentration. Both models were able to simulate soil salinity with good accuracy; thus, they can be used to manage salinity at field scale (Pourgholam-Amiji et al. 2021). Water and fertilizer management is important to get good crop yield and higher nitrogen use efficiency. Hence, Wu et al. (2022) developed a framework to simulate evapotranspiration under water and N stress in modified version of AquaCrop. The accurate performance of AquaCrop has shown that it can be used as a robust tool to develop precise managements for arid areas. Optimization of irrigation scheduling requires knowledge of crop and soil, which is possible through a decision support system. The AquaCrop and MOPECO models were used by Martínez-Romero et al. (2021) to optimize irrigation for barley crop. The results showed that both models were complementary to simulate gross irrigation water depths to attain the potential crop yield (e.g., 310 mm is required by barley to give potential yield). Rahimikhoob et al. (2021) applied AquaCrop a semiquantitative approach to simulate crop response to N stress using the critical N-concentration idea. Results depicted that direct simulation by using crop N status is a good option to improve soil fertility management. Biochar is a climate-friendly practice that can ensure food security by preventing water stress and fertilizer overuse. The AquaCrop model was used by Huang et al. (2022) to optimize the integrated strategies that involves irrigation, N, and biochar regimes. Results showed that AquaCrop simulated treatments impacts on crop yield with good accuracy. Hence, it can be used as a reliable tool for the optimization of field management, e.g., addition of fertilizer, biochar, and irrigation. Adeboye et al. (2019) evaluated AquaCrop to simulate soil water storage and water productivity of soybean. The model has shown low performance in simulating evapotranspiration and water productivity that needs to be fixed for dryland agriculture. AquaCrop-OSPy was proposed as an open source to be used to bridge the gap between research and practice (Kelly and Foster 2021). Groundnut is crop of dryland regions; hence, its simulation is tricky. Chibarabada et al. (2020) tested AquaCrop to simulate evapotranspiration, crop canopy cover, biomass, and yield under water stress conditions. Overall, the model shown good performance under water stress conditions, but it should be further tested under different soils and climates. Han et al. (2020) suggested that performance of crop models could be improved by upscaling the approach through remote sensing, as it can generate spatial distribution of crop parameters.

Soil organic carbon (SOC) is an important C pool, which can minimize atmospheric CO_2 concentration if managed properly. Wan et al. (2011) used the RothC model to study the impact of climate change on SOC stock. Results depicted that

SOC will decrease at higher rate in future if adaptation options, such as adding organic matter in soil through residues management and manure applications, will not be opted quickly. Furthermore, SOC could be increased by applying conservation agriculture practices, intercropping, cover cropping, and mixed farming. Lychuk et al. (2021) used the EPIC model to assess the losses of NO_3-N and labile P under changing climate, three levels of agricultural inputs (organic, reduced, and high), and three levels of cropping diversity (low, diversified annual crops, mixture of annual and perennial crops). Results showed that climate change resulted to the increase losses of NO_3-N, which can be mitigated by increasing cropping diversity as suggested in this work. LPJ-GUESS (Lund-Potsdam-Jena General Ecosystem Simulator) was used by Ma et al. (2022) to assess the impacts of agricultural managements on soil C stocks, nitrogen loss, and crop production. Conservation agriculture practices, i.e., no tillage, cover crop, residue, and manure application, have shown positive effect on SOC, while loss of N was also minimum under these practices. A hydro-biogeochemical model (SWAT-DayCent) was used to investigate the effect of climate warming and root zone soil water contents on SOC. Three Representative Concentration Pathways (RCP2.6, 4.5, and 8.5) and five global climate models were used in this study. The results showed that SOC will decrease in future due to higher warming but higher soil water content could depress SOC losses (Zhao et al. 2021).

Climate change will negatively affect SOM dynamics, soil organisms, and soil properties, but warmer conditions could lead to the higher availability of soil N due to higher mineralization rate. Hence, soil management particularly N application will be governed by future climate change (Jat et al. 2018). SOC dynamics is the core of interlinked environmental problems. However, its management is a mystery due to its complex relationship with N availability, moisture, and temperature. Srivastava et al. (2017) reviewed soil C dynamics under changing climate and suggested that soil may act as a potential C sink if managed properly (e.g., management of soil inorganic N pools and its proper linkage with microbial processes). Climate change mitigation is the implementation of efforts to halt or reverse climate change through behavior, technological, and management strategies (Fig. 3.21). With practical on ground mitigation practices, soil can play a role to reduce CO_2 emissions. It can be a carbon sink instead of the source (Lal 2004; Paustian et al. 2016). On the other hand, the adaptation is to achieve higher resilience toward extreme climatic events. It is possible through different managements as shown in Figure 3.21, which can improve SOC. This higher SOC will help to retain more water and could produce crops even under drought. Sustainable development goals (SDGs), which are the blueprint to achieve a sustainable future for all, could be achieved through improving SOC. The benefit of improvement of SOC to achieve SDGs is elaborated in Fig. 3.22. Mitigation and adaptation both offer solutions to climate change, and they are directly and indirectly related to SDGs. However, they are not always complementary as sometimes they can be independent from each other. Balanced fertilization is the key adaptation strategy, which can sustain SOC on long term basis. Mohanty et al. (2020) simulated C-sequestration potential of balanced fertilization (N and farmyard manure) in soybean-wheat cropping system using the

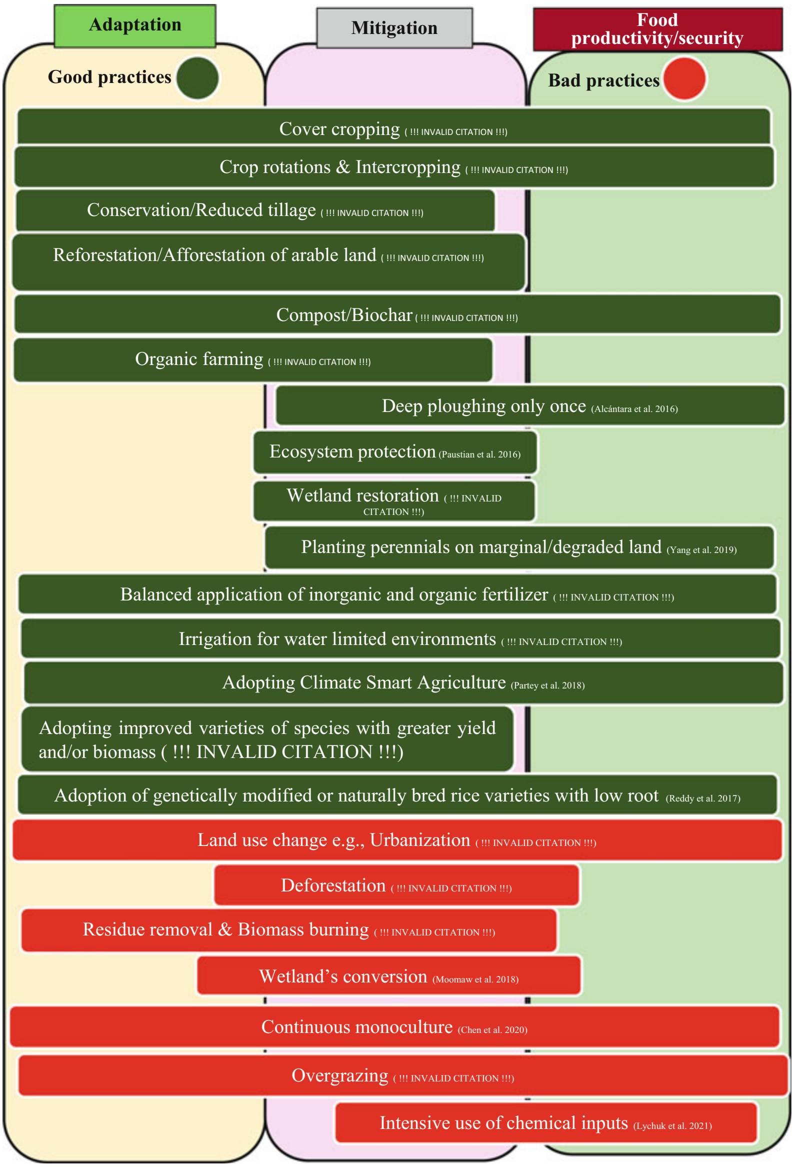


Fig. 3.21 Management strategies (Suggested and dissuaded) for the improvement of soil health and their impacts on climate change adaptation, mitigation, and food productivity/security

43-year long-term experimental dataset. The APSIM results showed that improved N and FYM management had the potential to increase SOC. Chaki et al. (2022) evaluated the APSIM potential to simulate conservation and conventional tillage practices in rice-wheat system. Results showed that the model was able to capture the

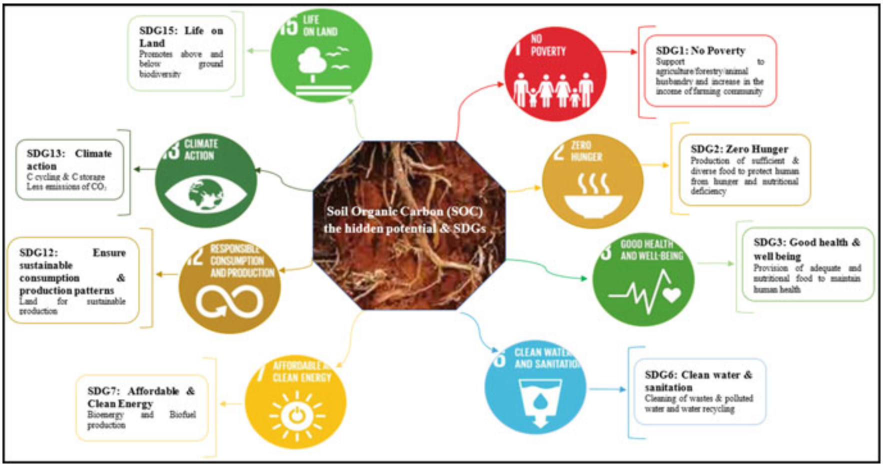


Fig. 3.22 Relationship between SOC and SDGs

effect of tillage, residue, N application, and cropping system; thus, it can be a good tool for designing the adaptation and mitigation options to climate change. Furthermore, the APSIM model was used evaluate the potential of conservation agriculture to mitigate climate change in water-scarce region Tunisia. Results depicted that mulching (residue retention) is more effective than conservation tillage under semi-arid and subhumid conditions. It can increase crop yield, WUE, and SOC as well as would help in the prevention of erosion (Bahri et al. 2019). Singh et al. (2022) compared the simulated potential of DRAINMOD-DSSAT and RZWQM2 to simulate the effects of management practices (N application rates and timings) on NO_3-N losses and crop yield. Results showed that both models provided the same conclusion for the N management strategy. Similarly, DSSAT was used as a valuable tool to suggest conservation agriculture as a potential way to adapt to climate change (Ngwira et al. 2014). Since process-based models are a good tool to design adaptation practices to climate change and, hence, to use them in real sense and to have true field picture, these models should be properly calibrated using different upscaling strategies (Chen et al. 2021).

3.6 Conclusion

Climate change is posing a major threat to food security through soil degradation. Since soil is the largest source of C, then it is necessary to conserve and improve SOM through its judicious use and management. Soil heath improvement will help to combat soil degradation, address food security, and mitigate climate change. Understanding and quantification of soil health through modern tools (e.g., remote sensing and modeling) are utmost important to design adaptation and mitigation strategies. Different adaptation and mitigation strategies are already available, which should be used to improve SOM. These includes reforestation, use of conservation tillage, intercropping, residue management, cover cropping, application of compost and biochar, balanced use of inorganic and organic fertilizer, and adoption of climate smart agriculture. However, these interventions need to be implemented properly through their dissemination to the real stakeholders, i.e., policy makers and farmers.

References

Abdollahi L, Munkholm LJ (2014) Tillage system and cover crop effects on soil quality: I. Chemical, mechanical, and biological properties. Soil Sci Soc Am J 78(1):262–270

Adeboye OB, Schultz B, Adekalu KO, Prasad KC (2019) Performance evaluation of AquaCrop in simulating soil water storage, yield, and water productivity of rainfed soybeans (Glycine max L. merr) in Ile-Ife, Nigeria. Agric Water Manag 213:1130–1146. https://doi.org/10.1016/j.agwat.2018.11.006

Alastal K, Ababou R (2019) Moving Multi-Front (MMF): a generalized Green-Ampt approach for vertical unsaturated flows. J Hydrol 579:124184. https://doi.org/10.1016/j.jhydrol.2019.124184

Alvar-Beltrán J, Heureux A, Soldan R, Manzanas R, Khan B, Dalla Marta A (2021) Assessing the impact of climate change on wheat and sugarcane with the AquaCrop model along the Indus River Basin. Pakis Agric Water Manag 253:106909. https://doi.org/10.1016/j.agwat.2021.106909

Amundson R, Biardeau L (2018) Soil carbon sequestration is an elusive climate mitigation tool. Proc Natl Acad Sci 115(46):11652–11656. https://doi.org/10.1073/pnas.1815901115

Angelopoulou T, Tziolas N, Balafoutis A, Zalidis G, Bochtis D (2019) Remote sensing techniques for soil organic carbon estimation: a review. Remote Sens 11(6):676

Badini O, Stöckle CO, Jones JW, Nelson R, Kodio A, Keita M (2007) A simulation-based analysis of productivity and soil carbon in response to time-controlled rotational grazing in the West African Sahel region. Agric Syst 94(1):87–96. https://doi.org/10.1016/j.agsy.2005.09.010

Bahri H, Annabi M, Cheikh M'Hamed H, Frija A (2019) Assessing the long-term impact of conservation agriculture on wheat-based systems in Tunisia using APSIM simulations under a climate change context. Sci Total Environ 692:1223–1233. https://doi.org/10.1016/j.scitotenv.2019.07.307

Bhatnagar R, Gohain GB (2020) Crop yield estimation using decision trees and random forest machine learning algorithms on data from terra (EOS AM-1) & Aqua (EOS PM-1) satellite data. In: Machine learning and data mining in aerospace technology. Springer, pp 107–124

Bird DN, Benabdallah S, Gouda N, Hummel F, Koeberl J, La Jeunesse I, Meyer S, Prettenthaler F, Soddu A, Woess-Gallasch S (2016) Modelling climate change impacts on and adaptation strategies for agriculture in Sardinia and Tunisia using AquaCrop and value-at-risk. Sci Total Environ 543:1019–1027. https://doi.org/10.1016/j.scitotenv.2015.07.035

Bretreger D, Yeo I-Y, Hancock G (2022) Quantifying irrigation water use with remote sensing: soil water deficit modelling with uncertain soil parameters. Agric Water Manag 260:107299. https://doi.org/10.1016/j.agwat.2021.107299

Brisson N, Mary B, Ripoche D, Jeuffroy MH, Ruget F, Nicoullaud B, Gate P, Devienne-Barret F, Antonioletti R, Durr C, Richard G, Beaudoin N, Recous S, Tayot X, Plenet D, Cellier P, Machet J-M, Meynard JM, Delécolle R (1998) STICS: a generic model for the simulation of crops and their water and nitrogen balances. I. Theory and parameterization applied to wheat and corn. Agronomie 18(5–6):311–346

Brisson N, Gary C, Justes E, Roche R, Mary B, Ripoche D, Zimmer D, Sierra J, Bertuzzi P, Burger P, Bussière F, Cabidoche YM, Cellier P, Debaeke P, Gaudillère JP, Hénault C, Maraux F, Seguin B, Sinoquet H (2003) An overview of the crop model stics. Eur J Agron 18(3–4):309–332. https://doi.org/10.1016/S1161-0301(02)00110-7

Campbell AD, Fatoyinbo T, Charles SP, Bourgeau-Chavez LL, Goes J, Gomes H, Halabisky M, Holmquist J, Lohrenz S, Mitchell C, Moskal LM, Poulter B, Qiu H, Resende De Sousa CH, Sayers M, Simard M, Stewart AJ, Singh D, Trettin C, Wu J, Zhang X, Lagomasino D (2022) A review of carbon monitoring in wet carbon systems using remote sensing. Environ Res Lett 17(2):025009. https://doi.org/10.1088/1748-9326/ac4d4d

Chahal I, Vyn RJ, Mayers D, Van Eerd LL (2020) Cumulative impact of cover crops on soil carbon sequestration and profitability in a temperate humid climate. Sci Rep 10(1):13381. https://doi.org/10.1038/s41598-020-70224-6

Chaki AK, Gaydon DS, Dalal RC, Bellotti WD, Gathala MK, Hossain A, Menzies NW (2022) How we used APSIM to simulate conservation agriculture practices in the rice-wheat system of the Eastern Gangetic Plains. Field Crop Res 275:108344. https://doi.org/10.1016/j.fcr.2021.108344

Chen S, He L, Cao Y, Wang R, Wu L, Wang Z, Zou Y, Siddique KHM, Xiong W, Liu M, Feng H, Yu Q, Wang X, He J (2021) Comparisons among four different upscaling strategies for cultivar genetic parameters in rainfed spring wheat phenology simulations with the DSSAT-CERES-wheat model. Agric Water Manag 258:107181. https://doi.org/10.1016/j.agwat.2021.107181

Chibarabada TP, Modi AT, Mabhaudhi T (2020) Calibration and evaluation of aquacrop for groundnut (Arachis hypogaea) under water deficit conditions. Agric For Meteorol 281: 107850. https://doi.org/10.1016/j.agrformet.2019.107850

Conant RT, Cerri CE, Osborne BB, Paustian K (2017) Grassland management impacts on soil carbon stocks: a new synthesis. Ecol Appl 27(2):662–668. https://doi.org/10.1002/eap.1473

Dalgaard T, Olesen JE, Petersen SO, Petersen BM, Jørgensen U, Kristensen T, Hutchings NJ, Gyldenkærne S, Hermansen JE (2011) Developments in greenhouse gas emissions and net energy use in Danish agriculture – how to achieve substantial CO_2 reductions? Environ Pollut 159(11):3193–3203. https://doi.org/10.1016/j.envpol.2011.02.024

de Wit A, Boogaard H, Fumagalli D, Janssen S, Knapen R, van Kraalingen D, Supit I, van der Wijngaart R, van Diepen K (2019) 25 years of the WOFOST cropping systems model. Agric Syst 168:154–167. https://doi.org/10.1016/j.agsy.2018.06.018

Diaz-Gonzalez FA, Vuelvas J, Correa CA, Vallejo VE, Patino D (2022) Machine learning and remote sensing techniques applied to estimate soil indicators – review. Ecol Indic 135:108517. https://doi.org/10.1016/j.ecolind.2021.108517

Donatelli M, Russell G, Rizzoli A, Acutis M, Adam M, Athanasiadis I, Balderacchi M, Bechini L, Belhouchette H, Bellocchi G, Bergez J-E, Botta M, Braudeau E, Bregaglio S, Carlini L, Casellas E, Celette F, Ceotto E, Charron-Moirez M, Confalonieri R, Corbeels M, Criscuolo L, Cruz P, di Guardo A, Ditto D, Dupraz C, Duru M, Fiorani D, Gentile A, Ewert F, Gary C, Habyarimana E, Jouany C, Kansou K, Knapen R, Filippi G, Leffelaar P, Manici L, Martin G, Martin P, Meuter E, Mugueta N, Mulia R, van Noordwijk M, Oomen R, Rosenmund A, Rossi V, Salinari F, Serrano A, Sorce A, Vincent G, Theau J-P, Thérond O, Trevisan M, Trevisiol P, van Evert F, Wallach D, Wery J, Zerourou A (2010) A component-based framework for simulating agricultural production and externalities. In: Brouwer FM, Ittersum MK (eds) Environmental and agricultural modelling. Springer Netherlands, pp 63–108. https://doi.org/10.1007/978-90-481-3619-3_4

Favoino E, Hogg D (2008) The potential role of compost in reducing greenhouse gases. Waste Manag Res 26(1):61–69. https://doi.org/10.1177/0734242x08088584

Forte A, Fiorentino N, Fagnano M, Fierro A (2017) Mitigation impact of minimum tillage on CO_2 and N_2O emissions from a Mediterranean maize cropped soil under low-water input management. Soil Tillage Res 166:167–178. https://doi.org/10.1016/j.still.2016.09.014

Gan Y, Liang C, Chai Q, Lemke RL, Campbell CA, Zentner RP (2014) Improving farming practices reduces the carbon footprint of spring wheat production. Nat Commun 5(1):5012. https://doi.org/10.1038/ncomms6012

Gassman PW, Williams JR, Wang X, Saleh A, Osei E, Hauck LM, Izaurralde RC, Flowers JD (2009) The agricultural policy environmental extender (APEX) model: an emerging tool for landscape and watershed environmental analyses. Trans ASABE 53:09-tr49

Ge Y, Thomasson JA, Sui R (2011) Remote sensing of soil properties in precision agriculture: a review. Front Earth Sci 5(3):229–238. https://doi.org/10.1007/s11707-011-0175-0

Gilhespy SL, Anthony S, Cardenas L, Chadwick D, del Prado A, Li C, Misselbrook T, Rees RM, Salas W, Sanz-Cobena A, Smith P, Tilston EL, Topp CFE, Vetter S, Yeluripati JB (2014) First 20 years of DNDC (DeNitrification DeComposition): model evolution. Ecol Model 292:51–62. https://doi.org/10.1016/j.ecolmodel.2014.09.004

Green W, Ampt G (1911) The flow of air and water through soils. J Agric Sci 4:1–24

Haddaway NR, Hedlund K, Jackson LE, Kätterer T, Lugato E, Thomsen IK, Jørgensen HB, Isberg P-E (2017) How does tillage intensity affect soil organic carbon? A systematic review. Environ Evid 6(1):30. https://doi.org/10.1186/s13750-017-0108-9

Han C, Zhang B, Chen H, Liu Y, Wei Z (2020) Novel approach of upscaling the FAO AquaCrop model into regional scale by using distributed crop parameters derived from remote sensing data. Agric Water Manag 240:106288. https://doi.org/10.1016/j.agwat.2020.106288

Harrington P (2012) Machine learning in action. Simon and Schuster

He Y, Zhou X, Jiang L, Li M, Du Z, Zhou G, Shao J, Wang X, Xu Z, Hosseini Bai S, Wallace H, Xu C (2017) Effects of biochar application on soil greenhouse gas fluxes: a meta-analysis. GCB Bioenergy 9(4):743–755. https://doi.org/10.1111/gcbb.12376

Hénault C, Germon JC (2000) NEMIS, a predictive model of denitrification on the field scale. Eur J Soil Sci 51(2):257–270. https://doi.org/10.1046/j.1365-2389.2000.00314.x

Huang M, Wang C, Qi W, Zhang Z, Xu H (2022) Modelling the integrated strategies of deficit irrigation, nitrogen fertilization, and biochar addition for winter wheat by AquaCrop based on a two-year field study. Field Crop Res 282:108510. https://doi.org/10.1016/j.fcr.2022.108510

IPCC (2001) Climate change 2001: the scientific basis. Contribution of Working Group I to the Third Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge

IPCC (2014) Climate change 2014: impacts, adaptation, and vulnerability. In: Field CB, Barros VR, Dokken DJ, Mach KJ, Mastrandrea MD, Bilir TE, Chatterjee M, Ebi KL, Estrada YO, Genova RC, Girma B, Kissel ES, Levy AN, MacCracken S, Mastrandrea PR, White LL (eds) Part A: global and sectoral aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge/New York

Izaurralde RC, Haugen-Kozyra K, Jans D, Mcgill WB, Grant R, Hiley J (2001) Soil C dynamics: measurement, simulation and site-to-region scale-up. Pacific Northwest National Lab (PNNL), Richland

Izaurralde RC, McGill WB, Williams JR (2012) Chapter 17 – development and application of the EPIC model for carbon cycle, greenhouse gas mitigation, and biofuel studies. In: Liebig MA, Franzluebbers AJ, Follett RF (eds) Managing agricultural greenhouse gases. Academic, San Diego, pp 293–308. https://doi.org/10.1016/B978-0-12-386897-8.00017-6

Jansson C, Faiola C, Wingler A, Zhu X-G, Kravchenko A, de Graaff M-A, Ogden AJ, Handakumbura PP, Werner C, Beckles DM (2021) Crops for carbon farming. Front Plant Sci 12. https://doi.org/10.3389/fpls.2021.636709

Jat ML, Bijay S, Stirling CM, Jat HS, Tetarwal JP, Jat RK, Singh R, Lopez-Ridaura S, Shirsath PB (2018) Chapter four – soil processes and wheat cropping under emerging climate change scenarios in South Asia. In: Sparks DL (ed) Advances in agronomy, vol 148. Academic Press, pp 111–171. https://doi.org/10.1016/bs.agron.2017.11.006

Jones CA (1986) CERES-Maize; a simulation model of maize growth and development. vol 04; SB91. M2, J6

Jones CD, Reddy AD, Jeong J, Williams JR, Hamilton SK, Hussain MZ, Bandaru V, Izaurralde RC (2021) Improved hydrological modeling with APEX and EPIC: model description, testing, and assessment of bioenergy producing landscape scenarios. Environ Model Softw 143:105111. https://doi.org/10.1016/j.envsoft.2021.105111

Jung J, Maeda M, Chang A, Bhandari M, Ashapure A, Landivar-Bowles J (2021) The potential of remote sensing and artificial intelligence as tools to improve the resilience of agriculture production systems. Curr Opin Biotechnol 70:15–22

Kale RV, Sahoo B (2011) Green-Ampt infiltration models for varied field conditions: a revisit. Water Resour Manag 25(14):3505. https://doi.org/10.1007/s11269-011-9868-0

Kaye JP, Quemada M (2017) Using cover crops to mitigate and adapt to climate change. A review. Agron Sustain Dev 37(1):4. https://doi.org/10.1007/s13593-016-0410-x

Kell DB (2011) Breeding crop plants with deep roots: their role in sustainable carbon, nutrient and water sequestration. Ann Bot 108(3):407–418. https://doi.org/10.1093/aob/mcr175

Kelly TD, Foster T (2021) AquaCrop-OSPy: bridging the gap between research and practice in crop-water modeling. Agric Water Manag 254:106976. https://doi.org/10.1016/j.agwat.2021.106976

Kowalska A, Pawlewicz A, Dusza M, Jaskulak M, Grobelak A (2020) Chapter 23 – plant–soil interactions in soil organic carbon sequestration as a restoration tool. In: Prasad MNV, Pietrzykowski M (eds) Climate change and soil interactions. Elsevier, pp 663–688. https://doi.org/10.1016/B978-0-12-818032-7.00023-0

Krauss M, Ruser R, Müller T, Hansen S, Mäder P, Gattinger A (2017) Impact of reduced tillage on greenhouse gas emissions and soil carbon stocks in an organic grass-clover ley – winter wheat cropping sequence. Agric Ecosyst Environ 239:324–333. https://doi.org/10.1016/j.agee.2017.01.029

Kroes J, Van Dam J, Groenendijk P, Hendriks R, Jacobs C (2009) SWAP version 3.2. Theory description and user manual. Alterra

Lal R (2004) Soil carbon sequestration impacts on global climate change and food security. Science 304(5677):1623–1627. https://doi.org/10.1126/science.1097396

Lal R (2005) Climate change, soil carbon dynamics, and global food security. Climate change and global food security. CRC Press, Boca Raton

Lal R (2008) Sequestration of atmospheric CO_2 in global carbon pools. Energy Environ Sci 1(1):86–100. https://doi.org/10.1039/B809492F

Lemaire G, Gastal F (1997) N uptake and distribution in plant canopies. In: Lemaire G (ed) Diagnosis of the nitrogen status in crops. Springer Berlin Heidelberg, Berlin/Heidelberg, pp 3–43. https://doi.org/10.1007/978-3-642-60684-7_1

Li CS (2000) Modeling trace gas emissions from agricultural ecosystems. Nutr Cycl Agroecosyst 58(1):259–276. https://doi.org/10.1023/A:1009859006242

Li C, Frolking S, Frolking TA (1992) A model of nitrous oxide evolution from soil driven by rainfall events: 1. Model structure and sensitivity. J Geophys Res Atmos 97(D9):9759–9776

Li S, Zheng X, Zhang W, Han S, Deng J, Wang K, Wang R, Yao Z, Liu C (2019) Modeling ammonia volatilization following the application of synthetic fertilizers to cultivated uplands with calcareous soils using an improved DNDC biogeochemistry model. Sci Total Environ 660:931–946. https://doi.org/10.1016/j.scitotenv.2018.12.379

Liu C, Cutforth H, Chai Q, Gan Y (2016) Farming tactics to reduce the carbon footprint of crop cultivation in semiarid areas. A review. Agron Sustain Dev 36(4):69. https://doi.org/10.1007/s13593-016-0404-8

Loureiro R, Prado FFD, Riggio G (2019) OMNICROP – an integrated systems alternative to ideal crop site localization and cultivation chamber self-management utilizing machine learning. J Crop Improv 33(1):110–124

Lychuk TE, Moulin AP, Lemke RL, Izaurralde RC, Johnson EN, Olfert OO, Brandt SA (2021) Modelling the effects of climate change, agricultural inputs, cropping diversity, and environment on soil nitrogen and phosphorus: a case study in Saskatchewan, Canada. Agric Water Manag 252:106850. https://doi.org/10.1016/j.agwat.2021.106850

Ma J, Rabin SS, Anthoni P, Bayer AD, Nyawira SS, Olin S, Xia L, Arneth A (2022) Assessing the impacts of agricultural managements on soil carbon stocks, nitrogen loss and crop production – a modelling study in Eastern Africa. Biogeosci Discuss 2022:1–31. https://doi.org/10.5194/bg-2021-352

Maiti SK, Ghosh D (2020) Chapter 24 – plant–soil interactions as a restoration tool. In: Prasad MNV, Pietrzykowski M (eds) Climate change and soil interactions. Elsevier, pp 689–730. https://doi.org/10.1016/B978-0-12-818032-7.00024-2

Mangalassery S, Sjögersten S, Sparkes DL, Sturrock CJ, Craigon J, Mooney SJ (2014) To what extent can zero tillage lead to a reduction in greenhouse gas emissions from temperate soils? Sci Rep 4(1):4586. https://doi.org/10.1038/srep04586

Martin SL, Clarke ML, Othman M, Ramsden SJ, West HM (2015) Biochar-mediated reductions in greenhouse gas emissions from soil amended with anaerobic digestates. Biomass Bioenergy 79: 39–49. https://doi.org/10.1016/j.biombioe.2015.04.030

Martínez-Romero A, López-Urrea R, Montoya F, Pardo JJ, Domínguez A (2021) Optimization of irrigation scheduling for barley crop, combining AquaCrop and MOPECO models to simulate various water-deficit regimes. Agric Water Manag 258:107219. https://doi.org/10.1016/j.agwat.2021.107219

Mattila TJ, Hagelberg E, Söderlund S, Joona J (2022) How farmers approach soil carbon sequestration? Lessons learned from 105 carbon-farming plans. Soil Tillage Res 215:105204. https://doi.org/10.1016/j.still.2021.105204

Mayer A, Hausfather Z, Jones AD, Silver WL (2018) The potential of agricultural land management to contribute to lower global surface temperatures. Sci Adv 4(8):eaaq0932. https://doi.org/10.1126/sciadv.aaq0932

McCann RJ, McFarland MA, Witz J (1991) Near-surface bare soil temperature model for biophysical models. Trans ASAE 34(3):748–0755. https://doi.org/10.13031/2013.31726

Mohanty M, Sinha NK, Somasundaram J, McDermid SS, Patra AK, Singh M, Dwivedi AK, Reddy KS, Rao CS, Prabhakar M, Hati KM, Jha P, Singh RK, Chaudhary RS, Kumar SN, Tripathi P, Dalal RC, Gaydon DS, Chaudhari SK (2020) Soil carbon sequestration potential in a Vertisol in Central India – results from a 43-year long-term experiment and APSIM modeling. Agric Syst 184:102906. https://doi.org/10.1016/j.agsy.2020.102906

Nguyen LTT, Kravchenko AN (2021) Effects of cover crops on soil CO_2 and N_2O emissions across topographically diverse agricultural landscapes in corn-soybean-wheat organic transition. Eur J Agron 122:126189. https://doi.org/10.1016/j.eja.2020.126189

Ngwira AR, Aune JB, Thierfelder C (2014) DSSAT modelling of conservation agriculture maize response to climate change in Malawi. Soil Tillage Res 143:85–94. https://doi.org/10.1016/j.still.2014.05.003

Nimah MN, Hanks RJ (1973) Model for estimating soil water, plant, and atmospheric interrelations: II. Field test of model. Soil Sci Soc Am J 37(4):528–532. https://doi.org/10.2136/sssaj1973.03615995003700040019x

Ogle SM, Alsaker C, Baldock J, Bernoux M, Breidt FJ, McConkey B, Regina K, Vazquez-Amabile GG (2019) Climate and soil characteristics determine where no-till management can store carbon in soils and mitigate greenhouse gas emissions. Sci Rep 9(1):11665. https://doi.org/10.1038/s41598-019-47861-7

Paustian K, Lehmann J, Ogle S, Reay D, Robertson GP, Smith P (2016) Climate-smart soils. Nature 532(7597):49–57

Paustian K, Larson E, Kent J, Marx E, Swan A (2019) Soil C sequestration as a biological negative emission strategy. Front Climate 1. https://doi.org/10.3389/fclim.2019.00008

Pourgholam-Amiji M, Liaghat A, Ghameshlou AN, Khoshravesh M (2021) The evaluation of DRAINMOD-S and AquaCrop models for simulating the salt concentration in soil profiles in areas with a saline and shallow water table. J Hydrol 598:126259. https://doi.org/10.1016/j.jhydrol.2021.126259

Rafique R, Kumar S, Luo Y, Xu X, Li D, Zhang W, Asam Z-u-Z (2014) Estimation of greenhouse gases (N2O, CH4 and CO2) from no-till cropland under increased temperature and altered precipitation regime: a DAYCENT model approach. Glob Planet Chang 118:106–114. https://doi.org/10.1016/j.gloplacha.2014.05.001

Rahimikhoob H, Sohrabi T, Delshad M (2021) Simulating crop response to nitrogen-deficiency stress using the critical nitrogen concentration concept and the AquaCrop semi-quantitative approach. Sci Hortic 285:110194. https://doi.org/10.1016/j.scienta.2021.110194

Rigon JPG, Calonego JC (2020) Soil carbon fluxes and balances of crop rotations under long-term no-till. Carbon Balance Manag 15(1):19. https://doi.org/10.1186/s13021-020-00154-3

Rosenberg NJ, McKenney MS, Easterling WE, Lemon KM (1992) Validation of EPIC model simulations of crop responses to current climate and CO_2 conditions: comparisons with census, expert judgment and experimental plot data. Agric For Meteorol 59(1–2):35–51. https://doi.org/10.1016/0168-1923(92)90085-I

Seligman N, Keulen H (1980) PAPRAN: a simulation model of annual pasture production limited by rainfall and nitrogen. In: Simulation of nitrogen behaviour of soil-plant systems. Pudoc, Wageningen, pp 192–221

Singh S, Negm L, Jeong H, Cooke R, Bhattarai R (2022) Comparison of simulated nitrogen management strategies using DRAINMOD-DSSAT and RZWQM2. Agric Water Manag 266: 107597. https://doi.org/10.1016/j.agwat.2022.107597

Smith P, Martino D, Cai Z, Gwary D, Janzen H, Kumar P, McCarl B, Ogle S, O'Mara F, Rice C (2008) Greenhouse gas mitigation in agriculture. Philos Trans R Soc Lond Ser B Biol Sci 363(1492):789–813

Smith W, Grant B, Desjardins R, Worth D, Li C, Boles S, Huffman E (2010) A tool to link agricultural activity data with the DNDC model to estimate GHG emission factors in Canada. Agric Ecosyst Environ 136(3–4):301–309

Spokas KA, Reicosky DC (2009) Impacts of sixteen different biochars on soil greenhouse gas production. Ann Environ Sci 3:4

Srivastava P, Singh R, Tripathi S, Singh P, Singh S, Singh H, Raghubanshi AS, Mishra PK (2017) Soil carbon dynamics under changing climate – a research transition from absolute to relative roles of inorganic nitrogen pools and associated microbial processes: a review. Pedosphere 27(5):792–806. https://doi.org/10.1016/S1002-0160(17)60488-0

Stockle CO, Williams JR, Rosenberg NJ, Jones CA (1992) A method for estimating the direct and climatic effects of rising atmospheric carbon dioxide on growth and yield of crops: part I – modification of the EPIC model for climate change analysis. Agric Syst 38(3):225–238. https://doi.org/10.1016/0308-521X(92)90067-X

Stöckle CO, Donatelli M, Nelson R (2003) CropSyst, a cropping systems simulation model. Eur J Agron 18(3–4):289–307. https://doi.org/10.1016/S1161-0301(02)00109-0

van Diepen CA, Wolf J, van Keulen H, Rappoldt C (1989) WOFOST: a simulation model of crop production. Soil Use Manag 5(1):16–24. https://doi.org/10.1111/j.1475-2743.1989.tb00755.x

Wan Y, Lin E, Xiong W, Ye L, Guo L (2011) Modeling the impact of climate change on soil organic carbon stock in upland soils in the 21st century in China. Agric Ecosyst Environ 141(1): 23–31. https://doi.org/10.1016/j.agee.2011.02.004

Williams JR (1990) The erosion-productivity impact calculator (EPIC) model: a case history. Philos Trans Biol Sci 329(1255):421–428. https://doi.org/10.2307/76847

Williams JR (1995) The EPIC model. In: Singh VP (ed) Computer models of watershed hydrology. Water Resources Publications, Colorado, pp 909–1000

Williams JR, Jones CA, Dyke PT (1984) A modeling approach to determining the relationship between erosion and soil productivity. Trans ASAE 27(1):129–144. https://doi.org/10.13031/2013.32748

Williams JR, Jones CA, Kiniry JR, Spanel DA (1989) The EPIC crop growth model. Trans ASAE 32(2):497–511. https://doi.org/10.13031/2013.31032

Wilson D, Blain D, Couwenberg J, Evans C, Murdiyarso D, Page S, Renou-Wilson F, Rieley J, Sirin A, Strack M (2016) Greenhouse gas emission factors associated with rewetting of organic soils. Mires Peat 17:222

Wu H, Yue Q, Guo P, Xu X, Huang X (2022) Improving the AquaCrop model to achieve direct simulation of evapotranspiration under nitrogen stress and joint simulation-optimization of irrigation and fertilizer schedules. Agric Water Manag 266:107599. https://doi.org/10.1016/j.agwat.2022.107599

Yang Y, Reilly EC, Jungers JM, Chen J, Smith TM (2019) Climate benefits of increasing plant diversity in perennial bioenergy crops. One Earth 1(4):434–445. https://doi.org/10.1016/j.oneear.2019.11.011

Zhang Y, Niu H (2016) The development of the DNDC plant growth sub-model and the application of DNDC in agriculture: a review. Agric Ecosyst Environ 230:271–282. https://doi.org/10.1016/j.agee.2016.06.017

Zhao F, Wu Y, Hui J, Sivakumar B, Meng X, Liu S (2021) Projected soil organic carbon loss in response to climate warming and soil water content in a loess watershed. Carbon Balance Manag 16(1):24. https://doi.org/10.1186/s13021-021-00187-2