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A Bayesian Belief Network framework to predict SOC dynamics of alternative management scenarios

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Abstract

Understanding the key drivers that affect a decline of soil organic carbon (SOC) stock in agricultural areas is of major concern since leading to a decline in service provision from soils and potentially carbon release into the atmosphere. Despite an increasing attention is given to SOC depletion and degradation processes, SOC dynamics are far from being completely understood because they occur in the long term and are the result of a complex interaction between management and pedo-climatic factors. In order to improve our understanding of SOC reduction phenomena in the mineral soils of Veneto region, this study aimed to adopt an innovative probabilistic Bayesian Belief Network (BBN) framework to model SOC dynamics and identify management scenarios that maximise its accumulation and minimise GHG emissions.

Results showed that the constructed BBN framework was able to describe SOC dynamics of the Veneto region, predicting probabilities of general accumulation (11.0%) and depletion (55.0%), similar to those already measured in field studies (15.3% and 50%, respectively). A general enhancement in the SOC content was observed where a minimum soil disturbance was adopted. This outcome suggested that management strategies of conversion from croplands to grasslands, no tillage and conservation agriculture are the most promising management strategies to reverse existing SOC reduction dynamics. Moreover, measures implying SOC stocks were also those providing major benefits in terms of GHGs reduction emissions. Finally, climate change scenarios slightly affected management practice. Advancements in our BBN framework might include more detailed classes at higher resolution as well as any socio-cultural or economic aspect that should improve the evaluation of prediction scenarios.

Keywords

Soil organic carbon; Agricultural management; Land use; Decision support system

1. Introduction

Soils are critical for the provision of economic goods and ecosystem services, including the accumulation of atmospheric carbon (Lal, 2010). However, there is growing concern among scientists and policy makers that soil organic carbon (SOC) is declining (Bouma, 2014; Stockmann et al., 2015), particularly in agricultural areas, leading to a decline in service provision from soils and potentially carbon release into the atmosphere (Koch et al., 2013; Smith, 2012). Monitoring changes in SOC content can help identify degrading soils in order to target them for management interventions that arrest declines and promote SOC accumulation.

Despite the attention that has been given to SOC (EC, 2012, Minelli et al., 2017), agricultural and environmental impacts as a result of SOC changes in Europe still have large uncertainties associated with them. These are dependent on several factors; economic (e.g., difficulty quantifying values of ecosystem services), ecological (e.g., uncertainty about climate change scenarios) or socio-cultural (e.g., willingness to adopt new technologies) (Burton and Schwarz, 2013; Smith et al., 2007a; Yigini and Panagos, 2016). At the local scale, long-term field studies have shown different SOC accumulation or depletion dynamics (Saby et al., 2008), mainly dependent on inherent pedologic and climatic conditions, land use intensity, and cropping systems management (Berti et al., 2016; Heikkinen et al., 2013; Maillard and Angers, 2014; Reijneveld et al., 2009). Predictions of SOC dynamics under different management strategies and/or climate scenarios have been extensively investigated using biogeochemical models (e.g., Borrelli et al., 2016; Lugato et al., 2014; Xu et al., 2011) at the large scale (from regional to trans-national). However, these models are limited if quantitative information is missing or uncertain.

Indeed, several SOM models rely on functional criteria related to microbial function (e.g. decay rate of C pools) with the aim of representing the effect of biochemical and physical factors on SOC turnover and C fluxes. However, as underlined by Dungait et al. (2012), the relative contribution of biochemical and physical controls on the decay are rarely tested empirically, instead, the weakness of a model's theoretical background is compensated for by calibration procedures. It follows that too often models are over-calibrated in order to operate effectively in the soil systems where they are validated. However, they are less consistent when applied to unusual soils or a different climate, at "the edge of, or beyond, their validation" range (Dungait et al., 2012, p. 1790).

For these reasons, environmental processes and management have been increasingly modelled following probabilistic approaches, where the uncertainty and variability of results is included in modelling (Uusitalo, 2007). Bayesian belief networks (BBNs) are probabilistic models that accommodate data uncertainty and variability and have increasingly been applied in ecological modelling since they are able to integrate both qualitative and quantitative variables in a unique model platform (Landuyt et al., 2013). By linking the different variables in a graphical interface, BBN users define cause-and-effect relationships that provide both diagnosis and prognosis under specific variable conditions, aiding the decision-making processing.

A first attempt to use BBNs to evaluate soil degradation was carried out by Hough et al. (2010) by modelling peat erosion in Scotland using a combination of a national soil properties inventory and local empirical observations. The authors identified climate variables the main factors associated with peat erosion, while a secondary role was associated with land management practices, in particular vegetation cover. Qualitative and quantitative information were merged also to evaluate the risk of soil compaction (Troldborg et al., 2013), although a lack of data for model validation (at field scale or from laboratory tests) partly weakened improvements in understanding factors (e.g., inherent soil characteristics, land management) and priorities to combat soil degradation.

In the Veneto region, north-eastern Italy, one of the most important impacts of intensive agriculture on arable soils is the decline of SOC content, estimated at average rates of 1.1 Mg ha^{-1} y^{-1} (Morari et al., 2006) as a result of continuous tillage, low organic inputs and over-simplification of cropping systems (i.e. monocultures). In this context policy makers, as well as land managers and scientists, need decision support tools to enable them to weigh up the benefits and drawbacks of different agricultural systems and to explore best agri-environmental management strategies.

According to previous European experiences on modelling soil properties with a probabilistic approach, it is expected that BBNs can provide new insights in soil management strategies. With the general purpose of evaluating the feasibility of simulating the C biogeochemical cycle using BBN models, this work aims: i) to quantify SOC accumulation and reduction in croplands and grasslands across the Veneto region, north-eastern Italy, after independent model validation; ii) to identify the main factors influencing SOC stock change dynamics; iii) to evaluate alternative management scenarios that maximise SOC accumulation and simultaneously minimise GHG emissions.

2. Material and methods

2.1 Study area

The Veneto region (NUTS-2, total area of 18,400 km^2) is located in north-eastern Italy, where 55% of the region is occupied by the Venetian plain, which is a complex system of urban, industrial, and intensive agricultural areas characterised by high population density. According to the last agricultural census (ISTAT, 2010), croplands and grasslands are mainly concentrated on the plain (78%), comprising mainly cereals (maize, wheat), soybean, and fodder crops (ca. 70% of total agricultural cultivations). Croplands and grasslands are generally irrigated where the shallow water table, mainly located in the low-lying area around the Venice lagoon, does not contribute to soil moisture in the root zone. A spatial visualisation of the Veneto region based on Corine Land Cover inventory (2012) is reported in Figure 1.

Most of the soils of the regional low plain (<15 m a.s.l.) are Calcisols and Cambisols characterised by sandy and silty-clay deposits with medium natural fertility deriving from low SOC content (usually in the range of 10-20 g kg^{-1}) and low cation exchange capacity. Luvisols and Cambisols (calcareous and skeletal loam, clay-loam soils) characterise mainly the high Venetian plain and hilly areas in the north (15-300 m a.s.l.), while Leptosols and Cambisols are alternated in the mountains, from sloping areas to valleys, respectively (WRB, 2014).

2.2 Bayesian Belief Network (BBN) model construction

A BBN model was built with the aim of combining the climate, biogeochemical and management drivers that influence SOC stock change in the 0-30 cm layer, according to the conceptual framework proposed in Morari et al. (2015). Drivers leading to changes in the SOC cycle were identified from either natural- or human-induced processes (e.g., net primary production, soil structure degradation), whose cause-and-effect relationships were identified after an iterative process that aimed to put theory into a regional context. Only agroecosystems including croplands and grasslands across the Veneto region were considered in this study. The target node was SOC stock change (Fig. 2), which considered climate, soil and management as the main group-factors comprising a total of 22 nodes and 30 links. According to Marcot et al. (2006), the number of nodes and their states was kept as low as possible in order to favour their tractability and understanding, while contemporarily describing SOC processes and SOC-related phenomena. In this context, some intermediate nodes were required to summarise nodes into major themes (e.g., endogen and hexogen carbon, soil fertility). Parentless input nodes represented the main geographic information associated with cropping systems and pedo-climatic parameters. The BBN model was built using Genie Academic 2.1 software (BayesFusion LLC, University of Pittsburgh, PA, USA).

2.3 BBN model parameterisation

Conditional probability tables (CPTs) were incorporated into the BBN model (each node was associated with a CPT) through available data, expert knowledge and existing models gathered from the literature and previous work conducted in the area, while parentless nodes had unconditional probability tables composed of prior knowledge on the frequencies of each state.

Parentless pedo-climatic nodes were populated using empirical evidence: in particular soil data from the Veneto Region 1:250,000 soil map (Regione Veneto, 2005), which is linked to an alphanumeric database with physicochemical characteristics (pH, texture, depth, intrinsic SOC content etc.). The database is regularly revised by the Veneto Region Environmental Protection Agency (ARPA Veneto), which provided an upgraded version of the database whose SOC data (0-3- cm soil layer) referred to the year 2010 (http://www.arpa.veneto.it/arpavinforma/indicatori-ambientali/indicatori_ambientali/geosfera/qualita-dei-suoli/contenuto-di-carbonio-organico-nello-strato-superficiale-di-suolo/view). The database did not include soil porosity information, which was estimated from bulk and particle density (Jury and Horton, 2004). Despite bulk density was present in the database and represent a key parameter to determine SOC stocks, here it is was not included among the basic parentless nodes. Firstly, because bulk density is correlated with soil texture properties and may represent a redundant information that is not needed in the BBN (Marcot et al., 2006). Secondly, because the aim of the work was to quantify the SOC stock change (rather than its absolute value), whose dynamic is not correlated with bulk density which was assumed a steady property.

The climatic database of Veneto used was that already adopted by Dal Ferro et al. (2016) in a study conducted in the same area and based on 35 meteorological stations evenly spread over the region, which provided 20 years of climatic data (1993-2013). Rainfall and reference evapotranspiration (ET_0), calculated using Penman-Monteith equation (Allen et al., 1998) by linking vegetation, temperature and time of year, were included as parentless nodes. Despite temperature is usually associated with crop biomass, in our BBN framework it was not explicitly used because implicitly included in the ET_0 node.

Parentless crops and fertiliser information were provided by the Veneto Region agricultural administration (Dal Ferro et al., 2016; Regione Veneto, 2012) at the municipal level. The database was used to describe cropland and grassland probability distributions across the region as well as type (organic or mineral) and quantity (kg ha^{-1} y^{-1}) of nutrient input. Irrigation was also included in the BBN model by considering the regional partition between irrigated and non-irrigated areas according to the ISTAT database (ISTAT, 2010).

Node-associated conditional probabilities were built using to a composite approach, in some cases using data derived by local field trials and modelling experiments while in others expert knowledge and literature review. In particular, data on soil tillage and cover crop practices were extracted from information on their spatial distribution across the Veneto region gathered through regional surveys carried out by the Rural Development Programme (Regione Veneto, 2013). Probability distributions of SOC turnover rate and crop biomass were derived from the modelling study of Dal Ferro et al. (2016) that was conducted in the Veneto region. Following Landuyt et al. (2016) these CPTs were determined based on the spatial relationship with associated parameters, such as soil fertility, ET_0, water supply, etc. (Table 1). In this context, soil moisture was not included to affect SOC dynamics because it is strictly related to soil texture. Similarly, soil nitrogen was also correlated with texture parameters and therefore not sensitive to change SOC. Nevertheless, experimental and modelling results showed that the fertiliser type, that in turn affected hexogen carbon, was the main factor to change soil carbon-nitrogen dynamics. According to Marcot et al., (2006), pedo-climatic and childe nodes were categorised by probabilistic state values (e.g., high, medium, low), defined through the conversion of continuous variables. The number of categories was kept the lowest as possible, although able to represent influences.

2.4 BBN scenarios

2.4.1 Land use and management

Land use and management scenarios, selected among others since the most promising and readily applicable in Europe to maintain SOC in agricultural soils (Morari et al., 2015; Powlson et al., 2011), have been hypothesised as the conversion from current agronomic conditions (hereafter called "standard scenario") to those adopting different strategies:

a. Croplands to 50% and alternatively 100% grassland: areas currently under arable production were converted to permanent grassland where grazing, hay making or mixed practices are generally applied;
b. Arable lands to 50% and alternatively 100% under no tillage practices: conventional practices, which usually include several tillage operations after crop harvest (mouldboard ploughing) and throughout the crop season (disk harrowing before sowing, hoeing, etc.), were converted to no tillage management;
c. Croplands to 50% and alternatively 100% of continuous soil cover with cover crops: this scenario simulated that cover crops followed the main crop in order to maintain continuous soil cover throughout the year. Cover crops were completely incorporated (i.e., used as green manure) into the soil;
d. Monoculture croplands to 50% and alternatively 100% under crop rotation: a succession of different crops including legumes in arable lands replaced intensive monoculture practices (mainly maize);
e. Croplands to 50% and alternatively 100% under conservation agriculture: following the regional guidelines that were proposed in the RDP 2007-2013 (Regione Veneto, 2013), this scenario was set up to predict the effects of conservation agriculture by including simultaneously crop rotation, cover crops and no tillage management practices;

f. Organic (farmyard manure) to 50% and alternatively 100% of total fertiliser input: an increase in the use of soil amendments (farmyard manure) was modelled as a substitute to mineral fertiliser.

2.4.2 Climate change scenarios

Projections of changes in climate, as provided by the Intergovernmental Panel on Climate Change (IPCC, 2007; IPCC, 2013), were combined with land use and management data in order to evaluate the effectiveness of potentially adopted strategies (see paragraph 2.4.1) to mitigate climate change. For this purpose, the quantification of greenhouse gas fluxes was included in the BBN model in terms of net carbon dioxide (CO_2), methane (CH_4) and nitrous oxide (N_2O) changes in agricultural fields. In particular, CO_2 was directly correlated with SOC dynamics, while CH_4 was associated with the degree of hexogen C input and rainfall, and N_2O was linked to fertilisers type and dose as well as climate conditions (i.e., temperature) (Smith et al., 2014; Smith et al., 2007b). Finally, GHGs emissions were converted into CO_2 equivalent (CO_2-eq) terms to enable an evaluation of integrated global warming potential (GWP) for CO_2 (GWP = 1), CH_4 (GWP = 28) and N_2O (GWP = 265) over a time horizon of 100 years (Smith et al., 2007b). Equivalent CO_2 emissions were modelled as utility values (Fig. 3), which refer to the combination of different management strategies with climate change emission scenarios as described in Nakicenovic et al. (2000). In particular, scenarios labelled as B1 ("Sustainable world", corresponding to atmospheric CO_2 concentration of 538 ppm), A1B ("Rich world", corresponding to CO_2 concentration of 674 ppm) and A2 ("Separated world", corresponding to CO_2 concentration of 754 ppm) were selected for comparison in this study. Some simplifications have been done: i) climate change effects were considered only in terms of rainfall and air temperature variations, neglecting the potential effects of CO_2 increase on other factors such as biomass yield; ii) only climate data without any further prediction on socio-cultural and economic change was considered; iii) CO_2-eq quantified only emissions from the biogeochemical cycles of different crop systems, thus excluding management aspects (e.g., machinery use) that directly contribute to changes in GHGs emissions; iv) despite the major contribution of rice paddy fields to GHGs emissions, they were not considered in the current analysis (ca. 0.9% of regional agricultural fields); v) potential adaptations of farm management systems (e.g. selection of new crop species and varieties, application of efficient irrigation methods) to climate change scenarios were not considered; vi) IPCC Special Report on Emission Scenarios (Nakicenovic et al., 2000), instead of the most recent IPCC Representative Concentration Pathways (IPCC, 2013), was used for consistency and comparison with previous studies (Lugato et al., 2015).

The stochastic weather generator LARS-WG (Semenov and Barrow, 2002) was used to produce a daily time series of climatic variables. Weather parameters were calibrated by using probability distributions of locally observed daily weather variables. Semi-empirical distributions of observed data were successively found, while Fourier series were used to describe precipitation amount, solar radiation, minimum and maximum temperatures. Finally, LARS-WG generated climate change weather data from multi-model ensemble of 15 climate models (Semenov et al., 2013) that were used in the IPCC 4th Assessment Report. In this context, the weather database for the Veneto region was used to describe alternative climate scenarios and evaluate their impact on CO_2-eq emissions.

2.5 BBN model validation

BBNs have been extensively used to evaluate ecosystem services and environmental management without any model validation, or simply based on stakeholder evaluation (Landuyt et al., 2013). However, assessing the ability of the model to represent target variables is a key step to providing reliable scenarios (Death et al., 2015), particularly in the case of SOC stock change, which is rather difficult to quantify without real-world data. Moreover, due to the low reactivity of SOC to management changes and high spatial variability, SOC dynamics should be evaluated in the medium/long term after stabilised management conditions, so as to reduce uncertainties in detecting changes in SOM stocks (Kuikman et al., 2012). In this context, the model was validated by comparing the BBN predictions on SOC stock change to a total of 212 unique values that were obtained from different case studies (Fig. 1). Field data (187 sampling points), collected in large plots (7.8 × 6 m) from a long-term experiment (established in 1962 and still ongoing) (Berti et al., 2016) were representative of different cropping systems (e.g. monoculture, crop rotation, grassland) and fertiliser inputs (e.g. mineral, organic, mixed) that are traditionally adopted across the Veneto region (Regione Veneto, 2012). The experiment is located at the experimental farm of the University of Padova (45° 20′ N 11° 18′ E, 6 m a.s.l.), characterised by a loamy Fluvi-Calcaric Cambisol. Agricultural practices that have only recently been introduced in the study area (i.e., no tillage, use of cover crops) were monitored in three different farms (69 sampling points) over a 3-year time span (Piccoli et al., 2016). The farms are located in three different areas of the Veneto region from east (Caorle municipality, 45° 38′ N 12° 57′ E, −2 m a.s.l.; silty-clay to sandy-loam, Gleyc Fluvisols or Endogleyc Flucic Cambisols) to centre (Mogliano Veneto municipality, 45° 35′ N 12° 18′ E, 6 m a.s.l.; silty-loam, Endogleyc Cambisols) and south-west (Ceregnano municipality, 45° 3′ N 11° 53′ E, 2 m a.s.l.; silty-loam, Endogleyc Cambisols) and well represented the pedo-climatic variability of the Venetian plain.

3. Results

3.1 Model validation and sensitivity analysis

In general, results showed that the BBN framework was reasonably accurate in modelling the SOC dynamics in the 0-30 cm profile (Fig. 4) since it was able to predict probabilities of general accumulation (11.0% vs. 15.3%) and depletion (55.0% vs. 50%) as already measured in the field. Small variations (-0.1 Mg ha^{-1} y^{-1} < SOC change < 0.1 Mg ha^{-1} y^{-1}) were also well described (34.0% vs. 34.7%). Nevertheless, by analysing SOC dynamics in detail, an overestimation was observed (18.0% vs 7.1%) of the "medium decrease" state value (-0.5 Mg ha^{-1} y^{-1} < SOC change < 1.0 Mg ha^{-1} y^{-1}), while extreme increases (> 1 Mg ha^{-1} y^{-1}) or decreases (< 1 Mg ha^{-1} y^{-1}) were negligible in both the real and modelled state.

Under standard land use and management conditions, the BBN model predicted that a moderate reduction in the SOC stock (here estimated in the range of 0.1 – 0.5 Mg C ha^{-1} y^{-1}) prevailed across the Veneto region, with a probability of 34% (Fig. 2), similar to the 33% estimated for the equilibrium in SOC dynamics (between -0.1 and 0.1 Mg C ha^{-1} y^{-1}). Further probabilities emphasised land degradation conditions (total 50%), while contrasting dynamics leading to SOC accumulation had a probability of only 17%, although in some cases they were estimated as greater than 1.0 Mg C ha^{-1} y^{-1}.

SOC stock change dynamics were the result of a complex interaction between management and pedo-climatic conditions. The influence of every node was calculated in Genie Academic 2.1 through a one-way sensitivity analysis, which estimated the spread of posterior probabilities of the specified target node (here SOC stock change) according to Castillo et al. (1997). In this context, field management practices, in particular the "Cropping system" and "Tillage operations", were the nodes that most strongly influenced SOC stock change (Table 2). A secondary role was provided by: i) the intrinsic SOC content (Table 2), which depended on the peculiar pedo-climatic condition of the region and was mainly classified as medium low (10-20 g kg^{-1}); ii) the SOC turnover coefficient, here generally implying SOC degradation conditions (89%) and associated with both pedo-climatic (soil texture, soil porosity, temperature) and management factors (soil disturbance by tillage). In contrast, the sensitivity analysis diagnosed negligible effects for soil-water factors (rainfall, irrigation) as well as nutrient quantity-related parameters (available N input, fertiliser dose), while their quality (e.g. organic amendments instead of mineral fertilisers) could partially modify SOC accumulation or depletion.

3.2 Soil management scenarios

A change in land use and management from standard conditions to soil-improving scenarios showed contrasting effects between different strategies. A general enhancement in the SOC content was observed when adopting practices of minimum soil disturbance as a consequence of conversion from croplands to grasslands, no tillage and conservation agriculture. Moreover, the modelled scenarios showed their ability to reverse the overall SOC dynamics trend, since all predicted a major accumulation that mainly offset the SOC reduction. In this context, croplands to grasslands, no tillage and conservation agriculture measures were able to increase the SOC content in the 0-30 soil layer, whether adopted on 50% (+29%, on average) or 100% (+57.7%, on average) of current arable land, with negligible differences between measures (Fig. 5). The estimated increase in SOC mainly involved medium (0.5 to 1.0 Mg ha^{-1} y^{-1}) and strong (>1.0 Mg ha^{-1} y^{-1}) improvements, overall reaching up to 60% of SOC stock change probability vs. 7% under the standard scenario.

By contrast, crop management strategies involving continuous soil cover and crop rotation showed only minor changes in the SOC dynamics of arable lands, highlighting the slight contribution of related nodes (e.g., organic carbon input from residues) as reported in the sensitivity analysis (Table 2). In particular, maintaining continuous soil cover through using cover crops, on both 50% and 100% of arable land, slightly reduced the probability of a SOC low decrease (-1%) towards equilibrium (no change, +1%), while crop rotation – instead of monoculture – led to some increase in medium SOC (+1%) in place of its general equilibrium (-1%).

Intermediate changes were observed when simulating a management change in fertiliser use, especially when farmyard manure was entirely (100%) adopted. Although SOC accumulation increased its overall probability by only 1% with respect to the standard scenario, the highest increase was observed for the most performing categories (i.e., high increase, +2%; medium increase, +1%) in place of minor changes for the others (i.e., no change, low increase). By contrast, this scenario highlighted weak capabilities to reverse overall SOC accumulation/reduction dynamics (Fig. 5).

3.3 GHGs emission scenarios

Impacts that might be generated by current and modelled management scenarios were evaluated in terms of CO_2 equivalents (CO_2-eq) and predicted in the context of climate change emissions scenarios (Table 3). In the standard scenario, state values of CO_2-eq balance from cropland and grassland showed net emissions, quantified at 1613.9 kg ha^{-1} y^{-1}, with major contributions of CO_2 and N_2O. In this context, estimated CO_2 fluxes from agricultural fields had 52% low emission probability (0-1000 kg C-CO_2 ha^{-1} y^{-1}), followed by 8% high (> 1000 kg C-CO_2 ha^{-1} y^{-1}), while those associated with N_2O were estimated 71% medium (1-3 kg N-N_2O ha^{-1} y^{-1}), 27% low (0-1 kg N-N_2O ha^{-1} y^{-1}) and finally 2% high (> 3 kg N-N_2O ha^{-1} y^{-1}). Methane emissions were always low (0-10 kg ha^{-1} y^{-1}). Modelled land use and management scenarios provided, in some cases, strong improvements in terms of GHGs emissions (e.g., minimum soil disturbance), while in others the difference with the standard scenario was negligible (e.g., continuous soil cover, conversion to organic input). In particular adopting no tillage, conversion from cropland to grassland and conservation agriculture (100% of the area) favoured net CO_2-eq adsorption dynamics (984 kg CO_2-eq ha^{-1} y^{-1}, on average), while 50% of their adoption involved lower equivalent CO_2 emissions (321 kg CO_2-eq ha^{-1} y^{-1}, on average) with respect to the standard scenario. Modelled land use and management strategies under climate change scenarios generally involved worsening conditions in terms of CO_2-eq emissions with respect to the current climatic conditions although always lower than 70 kg CO_2-eq ha^{-1} y^{-1} (Table 3). In particular, the higher temperatures affected an increase of N-N_2O emissions (the “High” class increased up to 5%, on average), offsetting a lowering of CO_2 emissions (ca. 1%) as a result of major endogen carbon inputs. By contrast, the BBN framework was seldom able to identify changes between rich (A1B), separate (A2) and sustainable (B1) world scenarios since differences were always ≤ 1.0 kg CO_2-eq ha^{-1} y^{-1}.

4. Discussion

The comparison of experimental results of SOC stock change with those from the developed Bayesian Belief Network suggests that the model performed well when evaluated with independent data, suggesting that the BBN was able to accurately describe the effects of different scenarios. Although BBNs work effectively with retrieval of partial data (Aguilera et al., 2011) it has also been recently reported in other studies (Death et al., 2015; Marcot, 2012) that steps leading to their accurate application should include independent validation to avoid bias in results as a consequence of expert, albeit subjective, knowledge.

As also observed in our study, in general the BBN simulation matched the general trend of SOC accumulation and depletion dynamics, whereas some specific classes ("medium decrease") were overestimated. This is likely due to some binding balance between requirements, on the one hand of detailed information, and on the other of simplification in the definition of state values and number of nodes. Predictions of SOC stock change across the Veneto region by the BBN model highlighted general soil degradation conditions, whose SOC reduction was quantified with high probability in the "Low increase" category (0.1-0.5 Mg C ha^{-1} y^{-1}). These results were similar to those reported in a study that was conducted in the same area using the DAYCENT biogeochemical model (Dal Ferro et al., 2016), showing average losses of 257 kg C ha^{-1} y^{-1} (0-20 cm layer), although with negative peaks lower than –4.0 Mg C ha^{-1} y^{-1} that were conversely not found here. Very few experimental results have assessed SOC stock changes on a large scale. Extensive field surveys on SOC content over the period 1979-2008 were combined with a geostatistical approach by Fantappiè et al. (2010) in an attempt to map Italian soil C dynamics. The authors, although with great uncertainties, reported SOC stock variations of between -1.5 Mg ha^{-1} y^{-1} and +1.5 Mg ha^{-1} y^{-1} (0-50 cm) for most soils in Veneto, emphasising that a dynamic SOC input-output equilibrium was far from being reached. In particular, they observed that land use type (e.g. cropland or grassland) was the most important factor leading to SOC variation, while a secondary role was associated with changes in land use intensity (e.g. crop system change). Similarly, the one-way sensitivity analysis (Table 2) showed that the type of cropping system per se and tillage operations, which are the factors that mainly characterise land use type (e.g. cropland instead of grassland), were primarily involved in SOC stock change dynamics, as also observed in long-term studies that have been conducted in north-eastern Italy (Morari et al., 2006). Improvements for SOC content were specifically modelled with the BBN through decreasing soil disturbance with zero-tillage (both in cropland and with the conversion to grassland) and maintaining a continuous soil cover (cover crops and grassland), although with contrasting results. Interestingly, only the omission of tillage operations was able to reverse the C dynamics trend from a general SOC reduction to major accumulation, although some SOC equilibrium/reduction phenomena were still likely. Maintaining continuous soil cover through cover crops had only a minor effect, even when its application was extended to 100% of arable lands. Mazzoncini et al. (2011) have reported contrasting results on the effects of cover crops on a loam soil in central Italy, where SOC increases were mainly observed in the soil surface layer (0-10 cm). However, these effects were observed some 15 years after the establishment of cover crops and the adoption of high nitrogen supply legume cover crops, which are seldom adopted in the Veneto region. In addition, a recent meta-analysis on SOC sequestration via cultivation of cover crops (Poeplau and Don, 2015) reported a mean annual accumulation rate of 0.32 ±0.08 Mg ha^{-1} y^{-1} (0-22 cm soil layer) in a time span of 54 years, in contrast to our findings. However, their study was conducted at the global scale including a wide variety of pedo-climatic conditions.

Findings on the different effects of no tillage and cover crops were combined with those from crop rotations in the conservation agriculture scenario, which showed comparable results to those reported for no tillage practices. As a consequence, general SOC improving conditions were partly mitigated by "No change" and "Low decrease" conditions. This was recently observed by Piccoli et al. (2016), although they also suggested that SOC stock changes should be evaluated over a deeper profile (50 cm) and longer periods of time to better evaluate the contribution of conservation practices to SOC accumulation or distribution, although the wide spatial variability could compensate the short-term period. Nevertheless, bias in our estimations cannot be completely excluded as our BBN model validation (Fig. 3) showed, in particular, some overestimation of SOC reduction rates. Moreover, the mismatch between SOC dynamics, derived from agricultural experimental studies, and their representativeness whether adopted at the large-scale is still debated, highlighting management and biological uncertainties on their real effectiveness (Smith et al., 2005). Finally, it must be noted that differences in soil sampling and quantification of SOC content may increase the uncertainty on SOC dynamics from field regional scale because of its nonlinear accumulation/decomposition rate (Six and Jastrow, 2002).

Measures for increasing soil carbon inputs with high refractory coefficients have been suggested to reduce SOC turnover and contribute to SOC stock. Recent findings (Berti et al., 2016; Kätterer et al., 2011) have confirmed that farmyard manure, among different hexogen C inputs, had the greatest potential in stabilising SOC content, since it shows the highest humification coefficient. In this context, a massive conversion of mineral nutrients input to organic amendments (farmyard manure) was hypothesised. Although the 100% application of farmyard manure instead of mineral fertiliser is not realistic, it was useful to investigate here to provide evidence on its effectiveness, since it is considered one of the best practices to increase SOC in mineral soils (Lal, 2004). Some benefits were observed in terms of SOC increases, especially at high rates (> 1.0 Mg ha^{-1} y^{-1}), likely influenced by sharp initial accumulations in arable soils of the low-lying plain that hardly receive organic amendments. Nevertheless, according to early studies on SOC stock scenarios (Smith et al., 1997), soils amended with organic manure has low C accumulation potential when compared to other management options (Fig. 5). In addition, care should be taken to consider the overall efficiency of the agricultural system when adopting organic inputs that might imply significant releases of nitrogen (N), especially in the low-lying Venetian plain that often has loose soils and a shallow water table, which makes it vulnerable to N leaching (Morari et al., 2012).

Climate variability, evaluated with the BBN in terms of climate change scenarios (temperature, rainfall and crop evapotranspiration), provided information on utility values of adopting different management strategies in terms of CO_2-eq emissions. The input-output CO_2-eq budget changed from current climatic conditions to those foreseen by the IPCC (Nakicenovic et al., 2000), on average by increasing the overall GHGs emissions as a result of increasing N_2O emissions, which counterbalanced reduced CO_2 emissions (from increased SOC stock) due to its greater global warming potential. However, the adoption of SOC-improving strategies (zero tillage, cropland to grassland, conservation agriculture) was still able to contribute actively to reducing GHGs emissions (Table 3). By contrast, marginal differences due to climate variability were observed since changing scenarios resulted in similar trends on GHGs emissions, as also reported in previous studies conducted at the European level (Lugato et al., 2014). Nevertheless, long-term validation is still required, especially for conservation agriculture practices, to evaluate possible changes on SOC and GHGs dynamics from short to long run.

These outcomes demonstrate that variability of management strategies across the Veneto region are likely to affect the SOC stock change more than climate variability, at least at the regional level (Table 2), thus emphasising the major contribution of CO_2, which is strictly related to SOC stock change (Fig. 3), to CO_2-eq emissions with respect to N_2O (Montzka et al., 2011). On the other hand, these results might have been affected by the sensitivity of the BBN model to slight variations in temperature and rainfall. Nevertheless, improvements in the BBN model (e.g., definition of more detailed classes, including experimental data at higher resolution) could overcome the low sensitivity to climate variability that was found, by providing more accurate outcomes as a result of slight variations in BBN parameters. Finally, at this stage the BBN framework did not take into account any socio-cultural or economic aspects that might affect economical support to farmers for soil-improving systems, the level of farmer expertise or technological developments leading to increased applicability and acceptance of sustainable land management practices. Nevertheless, it was largely achieved that BBNs can be used in an adaptive modelling framework that is often missing from traditional modelling approaches (Landuyt et al., 2013). Further work will be targeted to updating our framework to achieve socio-cultural and economic objectives.

5. Conclusions

The constructed BBN model well described the main management and climatic aspects related to SOC dynamics in croplands and grasslands across Veneto, showing its ability to act from farm (validation) to regional scale (consistent results with previous studies). By reflecting the variability of SOC dynamics in real world conditions and by including quali-quantitative information following a probabilistic approach, the BBN has proven to be a valuable decision support tool to distinguish the effect of different management practices. Strategies to reduce SOC depletion and soil degradation include minimum soil disturbance through no tillage and conversion from arable lands to grasslands. Covers crops, the use of organic amendments and crop rotation had only slight effects on SOC accumulation. In this context, the model was suitable to fill the gap between localised experimental studies and their extension to territorial application since including uncertainties that are usually not included in biogeochemical models. Finally, measures implying greater SOC stock were also those providing major benefits in terms of GHGs emissions. Further improvements should include socio-cultural and economic aspects, especially in the evaluation of prediction scenarios.

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List of figures

Figure 1 - Veneto region study area according to 2-level Corine Land Cover inventory (2012).

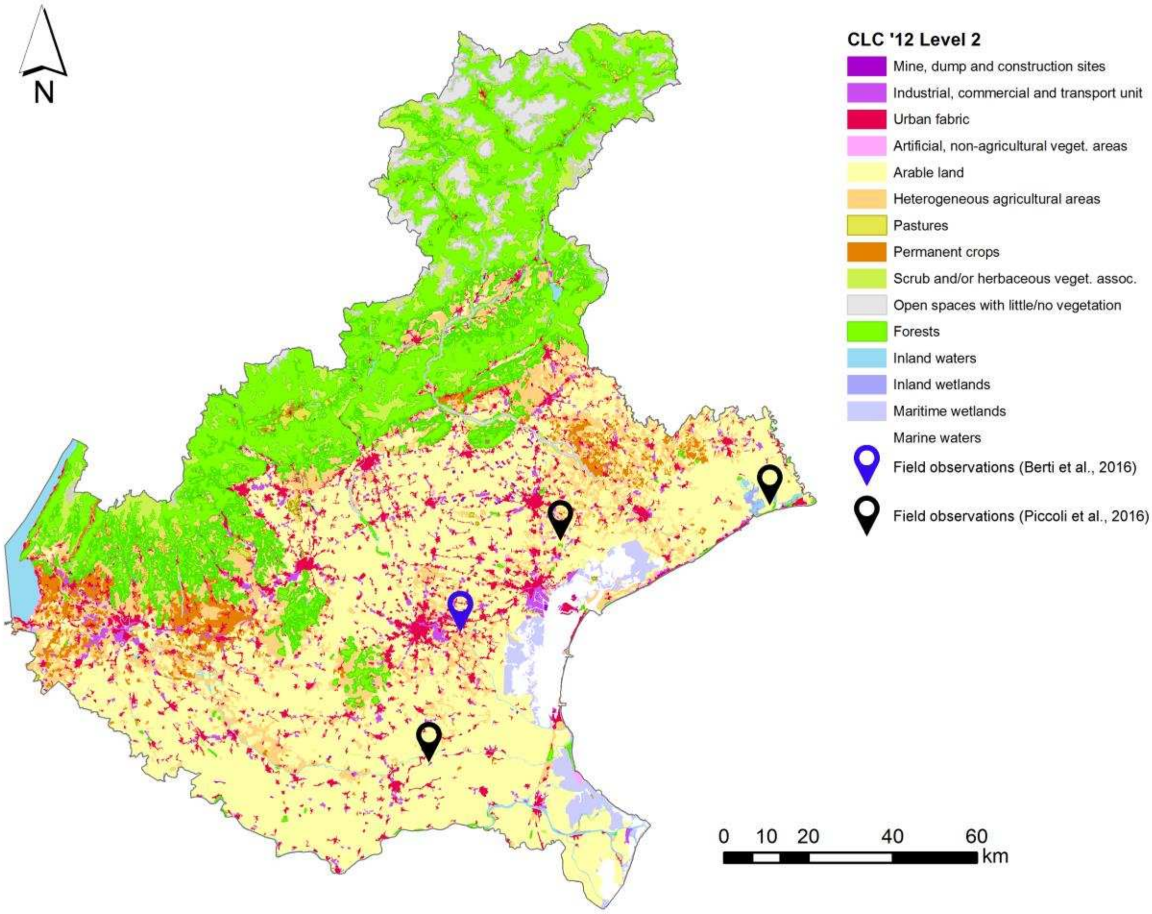


Figure 2 - Bayesian belief network showing factors determining SOC stock change in the 0-30 cm soil layer. Each node represents a specific factor that, interacting with other factors, influences the SOC stock change. The arrows represent the cause-and-effect direction between nodes. Each node can have a range of values (e.g. high, medium, low), each associated to a conditional probability.

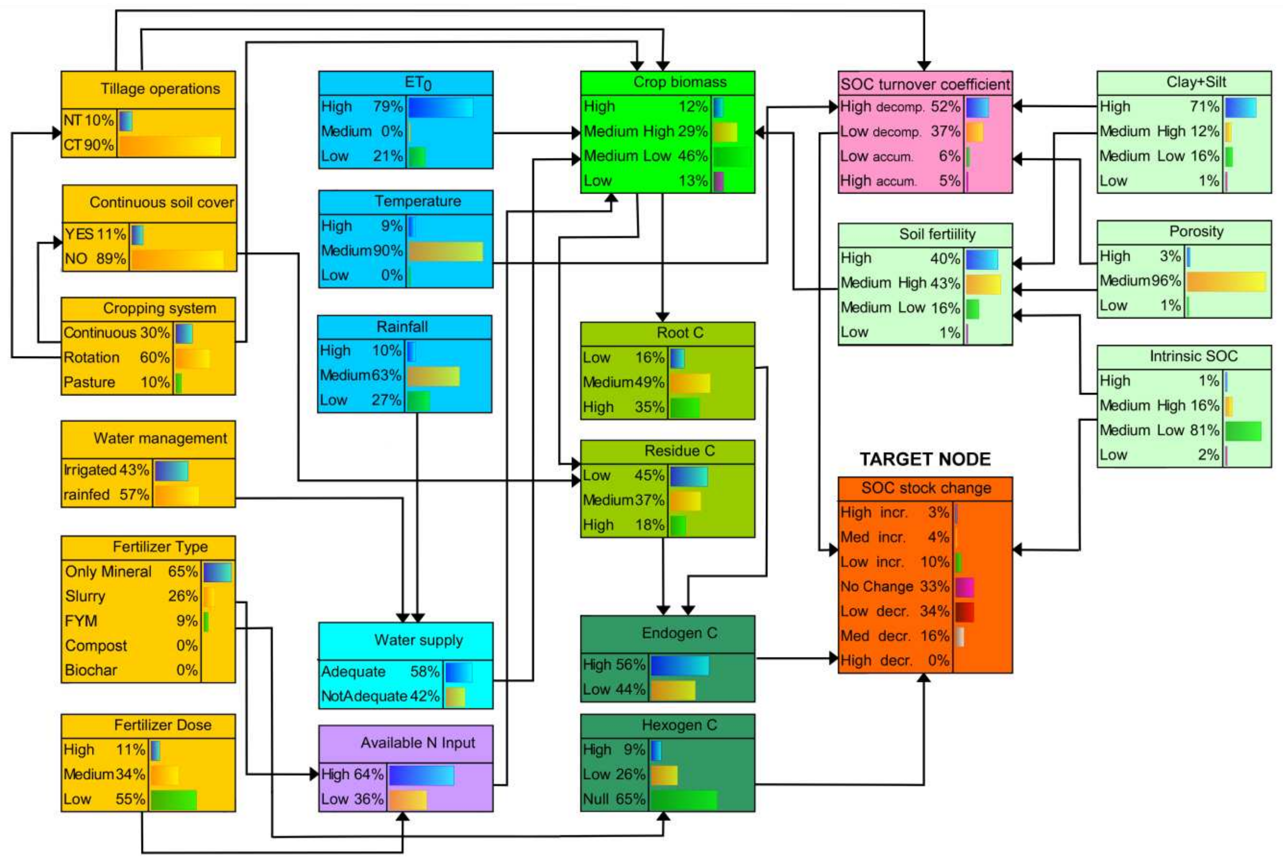


Figure 3 - BBN with utility values for climate change emissions scenarios.

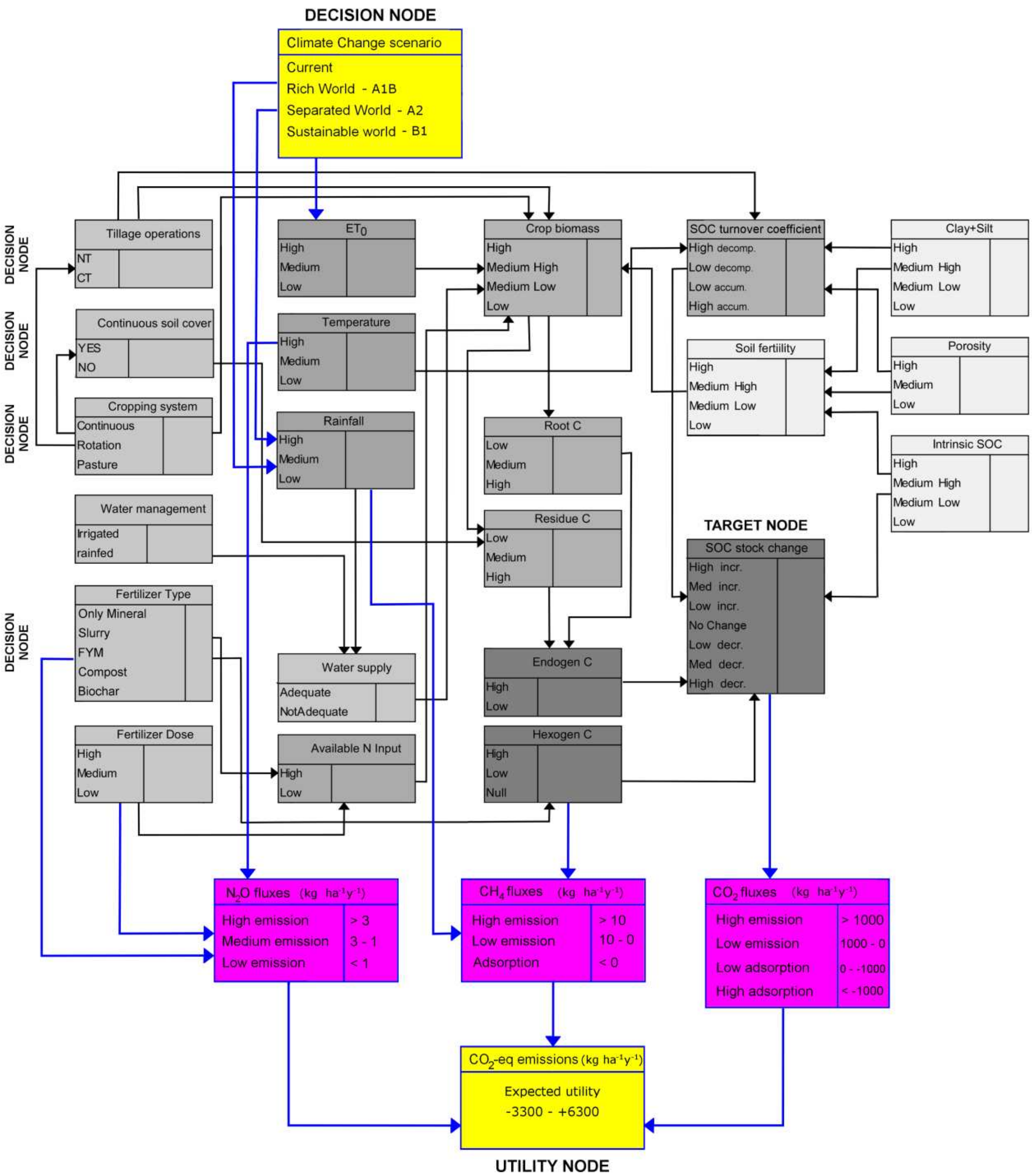


Figure 4 - Comparison of SOC stock change probability distributions as a result of field surveys and BBN modelling.

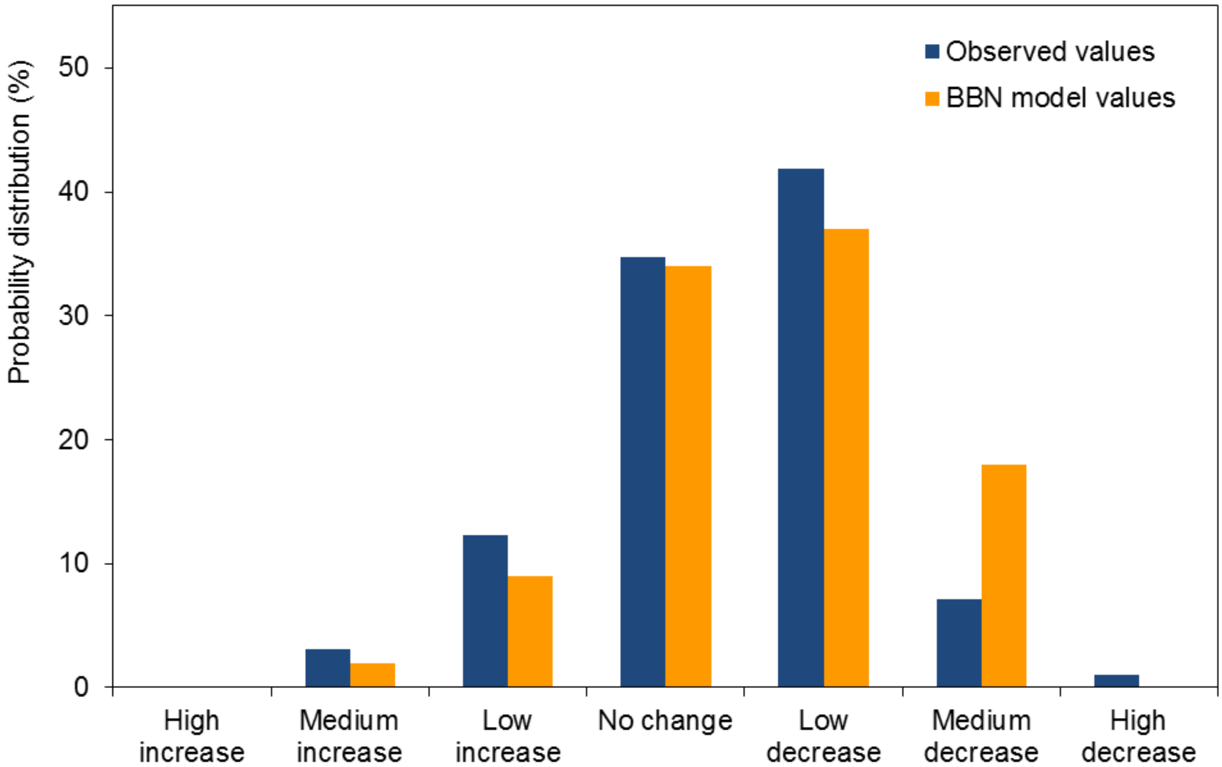
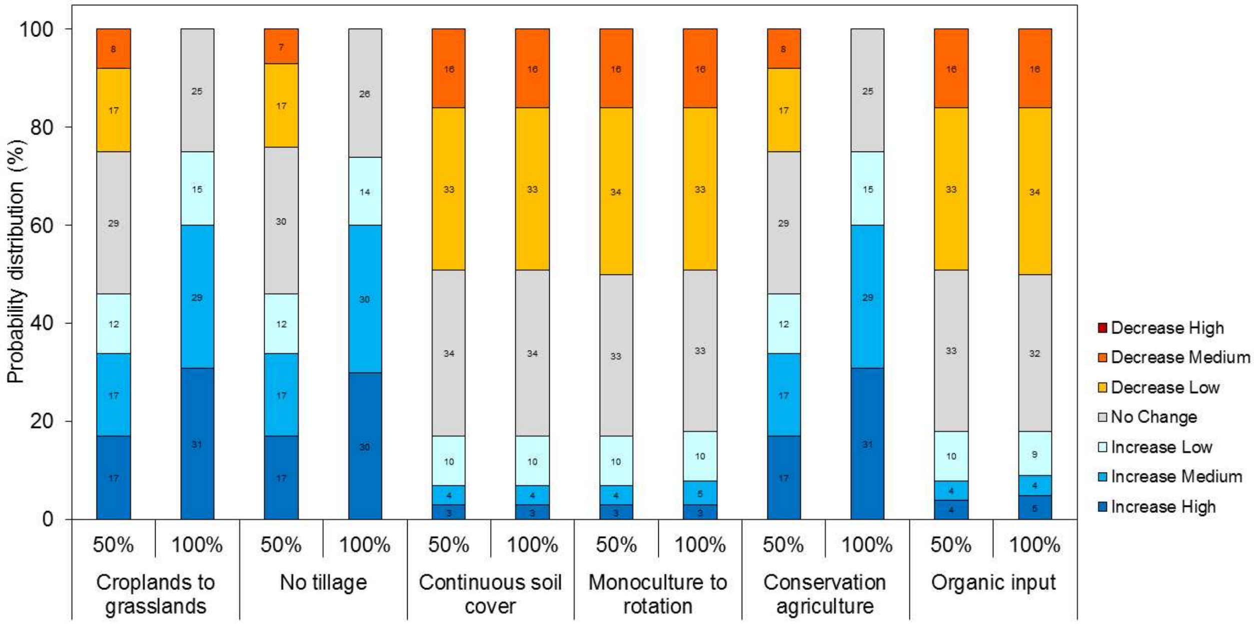


Figure 5 - SOC stock change probability distribution under different land use and management scenarios.



699 **Table 1** Description of nodes included in the BBN their state values to evaluate SOC stock change.

	Node	State value	Value/Description	Type of information
Pedo-climatic nodes	Intrinsic SOC content ($g\ kg^{-1}$)	High	> 40	Soil map (Regione Veneto, 2005)
		Medium high	40 – 20	
		Medium Low	20 – 10	
		Low	< 10	
	Soil porosity ($m^3\ m^{-3}$)	High	> 0.55	Soil map (Regione Veneto, 2005)
		Medium	0.55 – 0.40	
		Low	< 0.40	
	Clay + Silt ($kg\ kg^{-1}$)	High	> 0.6	Soil map (Regione Veneto, 2005)
		Medium high	0.6 – 0.4	
		Medium low	0.4 – 0.2	
		Low	< 0.2	
	ET_0 (mm)	High	> 1000	derived from Penman-Monteith equation on data from the Environmental Protection Agency (ARPAV)
		Medium	1000 – 800	
		Low	< 800	
	Rainfall (mm)	High	> 1200	Environmental Protection Agency (ARPAV)
		Medium	1200 – 1000	
		Low	< 1000	
	Temperature (°C)	High	> 13	Environmental Protection Agency (ARPAV)
		Low	< 13	
Management nodes	Crop system	Grassland		Regione Veneto (2012)
		Rotation		
		Monoculture		
	Fertiliser type	Mineral		Regione Veneto (2012)
		Slurry		
		Farmyard manure		
		Biochar		
		Compost		
	N fertiliser dose ($kg\ ha^{-1}\ y^{-1}$)	High	> 340	Regione Veneto (2012)
		Medium	340 – 170	

		Low	< 170	
	Tillage operation	Tillage		Regione Veneto (2013)
		No tillage		
	Continuous soil cover	Yes		Regione Veneto (2013)
		No		
	Water management	Irrigated		ISTAT, 2010
		Rainfed		
Child nodes	Available N input ($kg\ ha^{-1}$)	High	> 200	Expert opinion
		Low	< 200	
	Crop biomass ($Mg\ ha^{-1}$ d.m.)	High	> 30	Dal Ferro et al., 2016
		Medium high	30 – 20	
		Medium low	20 – 10	
		Low	< 10	
	Endogen OC input ($Mg\ ha^{-1}\ y^{-1}$)	High	> 4.0	Expert opinion
		Low	< 4.0	
	Hexogen OC input ($Mg\ ha^{-1}\ y^{-1}$)	High	> 4.0	Expert opinion
		Low	0.0 – 4.0	
		Null	0.0	
	Root carbon ($Mg\ ha^{-1}\ y^{-1}$)	High	> 4.0	Expert opinion
		Medium	4.0 – 2.0	
		Low	< 2.0	
	Residue carbon ($Mg\ ha^{-1}\ y^{-1}$)	High	> 4.0	Expert opinion
		Medium	4.0 – 2.0	
		Low	< 2.0	
	SOC turnover coefficient (y^{-1})	High decomposition	> 0.02	Six and Jastrow, 2002
		Low decomposition	0.0 – 0.02	
		Low accumulation	0.0 – -0.02	
		High accumulation	< -0.02	
	Soil fertility	High		Literature review; Expert opinion
		Medium high		
		Medium low		
		Low		

Water supply	Adequate		Literature review; Expert opinion
	Not adequate		
SOC stock change	High increase	> 1.0	
(Mg ha^{-1} y^{-1})	Medium increase	1.0 – 0.5	
SOC stock change	Low increase	0.5 – 0.1	Dal Ferro et al., 2016
(Mg ha^{-1} y^{-1})	No change	0.1 – -0.1	
	Low decrease	-0.1 – -0.5	
	Medium decrease	-0.5 – -1.0	
	High decrease	< -1.0	

Table 2 One-way sensitivity analysis of posterior probabilities for the node SOC stock change.

Order	Node	Sensitivity node
1	Cropping system	0.374
2	Tillage operations	0.226
3	Intrinsic SOC	0.139
4	SOC turnover coefficient	0.049
5	Fertiliser type	0.027
6	Clay+Silt	0.021
7	Endogen C	0.016
8	Porosity	0.015
9	Residue C	0.010
10	Hexogen C	0.009
11	Temperature	0.006
12	Fertiliser dose	0.005
13	Soil cover	0.004
14	Root C	0.004
15	Rainfall	0.001
16	Water management	0.001
17	Water supply	0.001
18	Soil fertility	0.001
19	Crop biomass	0.001
20	ET_0	0.000
21	Available N input	0.000

Table 3 Utility values of equivalent CO_2 emissions (CO_2-eq, kg ha^{-1} y^{-1}) under different land use and management and climate scenarios. The higher are the values, the greater are the CO_2-eq emissions.

Land use and management	Area investment	Climate scenarios			
		Current	Rich – A1B	Separate – A2	Sustainable – B1
Standard		1613.9	1647.2	1646.3	1647.2
Croplands to grasslands	50%	311.4	361.9	361.9	361.9
	100%	-991.0	-923.4	-922.4	-923.4
No tillage	50%	326.7	378.1	378.1	378.1
	100%	-972.9	-904.3	-904.3	-904.3
Continuous soil cover	50%	1617.7	1651.0	1651.0	1651.0
	100%	1621.5	1656.7	1656.7	1656.7
Monoculture to rotation	50%	1613.9	1647.2	1647.2	1646.3
	100%	1612.0	1645.3	1645.3	1645.3
Conservation agriculture	50%	324.8	376.2	376.2	376.2
	100%	-990.1	-923.4	-923.4	-923.4
Organic input	50%	1604.3	1643.4	1643.4	1643.4
	100%	1558.6	1588.1	1588.1	1588.1