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Application of CarboSOIL model to predict the effects of climate change on soil organic carbon stocks in agro-silvo-pastoral Mediterranean management systems

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Abstract

CarboSOIL model and climate outputs from two GCMs (GISS and HadCM3), three time horizons (2020, 2050, 2080), and two emission scenarios (A2 and B2) according to IPCC were used to study the effects of climate change on SOC dynamics in a Mediterranean region (Northeast Sardinia, Italy). CarboSOIL is an empirical model based on regression techniques and developed to predict SOC contents at standard soil depths of 0-25, 25-50 and 50-75 cm. The area is characterized by extensive agro-silvo-pastoral systems, and six land uses with different levels of cropping intensification were compared: Tilled vineyards (TV), No-tilled grassed vineyards (GV), Hay crop (HC), Pasture (PA), Cork oak forest (CO), and Semi-natural systems (SN). The main objectives were: i) to validate the model predictions with the measured SOC stocks, and ii) to predict SOC changes in future climate projections for the different land use types.

The model proved its ability to predict SOC stocks at different soil depths, and can be used as a tool for predicting SOC changes under different climate change scenarios.

The results suggest that future climatic scenarios can have a negative effect on SOC stocks in the upper sections of the soil profile, mainly due to a very low increase in the 0-25 cm section and a sharp decrease in the 25-50 cm soil section, in particular in a long term perspective (2080) and under the emission scenario A2.

Important decreases of SOC stocks were found in the upper soil sections of the vineyards.

Keywords: Mediterranean systems, soil organic carbon, climate change, emission scenarios, land use, CarboSOIL

1. Introduction

Soil organic carbon (SOC) positively affects soil functions with regard to habitat, biological diversity, soil fertility, crop production potential, erosion control, water retention, exchange of gases and chemicals between soil, atmosphere and water, and the filtering, buffering and transforming capacity (Huber et al., 2001; Kirchmann and Andersson, 2001).

Since soil organic matter (SOM) is constantly built up and decomposed, SOC contained in the organic matter is released to the atmosphere as CO_2 and recaptured through photosynthesis. Soil C sequestration is achieved by increasing the net flux of C from the atmosphere to the terrestrial biosphere, by storing more of the C from net primary production in the longer-term C pools in the soil, or by slowing down decomposition (Smith, 2005). As a consequence, C sequestration via agricultural soils has a potential to contribute significantly to climate change mitigation, and can be affected by management practices (Conant et al., 2001).

Many studies have focused on SOC distribution in biologically active layers of topsoil, where SOC and nutrient cycling is most dynamic (Jarecki and Lal, 2005; Wright et al., 2007; Yoo et al., 2006; Young et al., 2005). But a global consensus is still lacking about the depth to which SOC and other soil parameters should be measured and modelled, and how climate affect SOC distribution down the soil profile (Grüneburg et al., 2010; Li et al., 2007; Malmoud et al., 2009).

The IPCC carbon accounting method estimates the change in SOC storage for the top 30 cm of a soil profile (IPCC, 2006), but questions remain as to SOC concentrations below this depth (Don et al., 2007).

SOC estimates are more uncertain in areas with heterogeneous land uses and pedoclimatic conditions as Mediterranean environments, which are more prone to land degradation due to the combined effect of high temperatures during the summer, which enhance SOC degradation and depletion, and erosive processes on the hills due to heavy rains in winter (Cerda et al., 2010). Indeed, these effects will be enhanced by global warming and climate change.

Most of the known factors acting on SOC dynamics have been implemented in simulation models which take into account the interactions among climate, pedology, cropping system, soil and crop management (Francaviglia et al., 2012). Moreover, well-validated models can be used to predict SOC changes under different management and climatic conditions that may occur in the future (Jones and Donnelly, 2004). Among SOC models, CENTURY (Parton et al., 1994) and RothC (Coleman and Jenkinson, 1996) are particularly suitable to describe the turnover of the different SOC pools. Both models have been extensively applied worldwide under a variety of pedoclimatic and cropping conditions, and have a similar structure, containing pools with a rapid turnover (month-year), moderate turnover (decadal), and slow turnover (millennial or inert). The first model is more complex and requires a high number of input parameters, while the second requires a low number of parameters easy to be collected, but it only simulates processes in the topsoil layer (e.g. 20-25 cm).

Both models have been applied in the Mediterranean region to simulate SOC changes (Alvaro-Fuentes et al., 2012; Francaviglia et al., 2012; Lugato and Berti, 2008; Mondini et al., 2012). Nonetheless, few modelling studies consider different soil layers or the entire profile in the assessment of projected SOC stocks under climate change in the Mediterranean region (Bernardoni et al., 2012; De Sanctis et al., 2012; Farina et al., 2011; Muñoz-Rojas et al., 2013).

In this study, the CarboSOIL model (Muñoz-Rojas et al., 2013) together with climate outputs from two GCMs (GISS and HadCM3), three time horizons (2020, 2050, 2080), and two emission scenarios (A2 and B2) according to Intergovernmental Panel on Climate Change (IPCC, 2007) was used to study the effects of climate change on SOC dynamics in a Mediterranean region (Northeast Sardinia, Italy); the area is characterized by extensive agro-silvo-pastoral systems typical of similar areas of the Mediterranean basin. CarboSOIL is an empirical model based on regression techniques and developed to predict SOC contents at standard soil depths of 0-25, 25-50 and 50-75 cm (Muñoz-Rojas et al., 2013). The main objectives were: i) to validate the model predictions with the measured SOC stocks, and ii) to predict SOC changes in future climate projections for the different land use types.

2. Materials and methods

2.1 Model description

CarboSOIL was developed to predict SOC stocks and changes in Mediterranean areas under different scenarios of climate and land use at different soil depths (Muñoz-Rojas et al, 2013) and it has been incorporated in the land evaluation decision support system MicroLEIS DSS (De la Rosa et al., 2004).

The model consists of four modules or submodels that predict soil organic carbon contents at different depths: (a) CarboSOIL25 (0–25 cm), (b) CarboSOIL50 (25–50 cm) and (c) CarboSOIL75 (50–75 cm). The required input parameters include (I) climate variables (mean winter/summer temperature and annual precipitation), (II) site variables (elevation, slope, erosion, type of drainage), (III) soil (pH, N, cation exchange capacity, sand/clay content, bulk density and field capacity), and (IV) land use, with a total of 15 independent variables and soil organic carbon as predictor variable (Table 1).

A dataset with detailed description of 1756 soil profiles was used for the design of CarboSOIL, which was built as an empirical model based on multiple linear regression and Box–Cox transformation techniques (Muñoz-Rojas et al., 2013).

2.2 Study area

CarboSOIL model was applied to an area of about 1450 ha (Fig. 1) in north-eastern Sardinia (Italy) (40°46’N, 9°10’E, mean altitude 285 m a.s.l.), characterized by extensive agro-silvo-pastoral systems typical of similar areas of the Mediterranean basin (e.g. the Iberian Peninsula).

The local climate is warm temperate with dry and hot summers, with a mean annual rainfall of 623 mm (range 367–811 mm) and mean annual temperature of 15.0°C (13.8–16.4°C).

Soils are Dystric Endoleptic Cambisols (WRB, 2014), while cork oak forest (*Quercus suber* L.) is the potential native vegetation which has been converted to managed land with pastures and vineyards in recent years (Lagomarsino et al., 2011; Francaviglia et al., 2012; Bagella et al, 2013a,b; Francaviglia et al., 2014). Six land uses with different levels of cropping intensification were compared: Tilled vineyards (TV), No-tilled grassed vineyards (GV), Hay crop (HC), Pasture (PA), Cork oak forest (CO), and Semi-natural systems (SN).

TV is ploughed every year to 40 cm, is under organic farming management, but pruning residues are removed from the field. GV is grassed, the pruning residues are left on the soil, and supplementary drip irrigation is applied in summer if needed. The HC land use is cereals and annual legumes for 5 years for hay production, and intercropped by spontaneous herbaceous vegetation in the sixth year. It is ploughed to 40 cm and grazing is allowed with 3-4 sheep ha^{-1}. The PA land use is 5 years of spontaneous herbaceous vegetation, and one year of intercropping with a hay crop. It is tilled 1 year out of 6 and is grazed with 6 sheep ha^{-1}. The CO land use represents the natural vegetation of the area, and is used for cork production and cattle grazing (1.5 heads ha^{-1}) in the clearings. The SN land use (Mediterranean maquis and scrublands, and thermophilous meadows with Helichrysum) arise from the natural re-vegetation of former vineyards set-aside about 30 years ago.

Both PA and HC include scattered cork-oak stands, which are key components of the “Dehesa” agroforestry system (grazing system with Quercus L.) typical of other areas of southern Mediterranean Europe (Portugal and Spain). Dehesas are often converted to more profitable land uses such as vineyards (Francaviglia et al., 2012; Muñoz-Rojas et al., 2013) or olive groves (Lozano-García and Parras-Alcántara, 2013).

2.3 Soil sampling and analyses

The six land uses are common in the study area, but samplings refer to smaller monitoring areas chosen on existing available soil surveys, which indicated that the spatial variability of SOC was mainly due to land uses and within them by a different land cover condition, since climatic and pedologic conditions were the same. Specific soil sampling was carried out in 2007 in the selected monitoring areas as described by Francaviglia et al. (2014) considering the land cover condition. Briefly, the more heterogeneous land uses were sampled along and between the rows (TV and TG), and in areas covered by trees and open areas (PA and HC). SN was sampled in different conditions of vegetation cover due to the existence of heterogeneous natural vegetation. In the CO land use the soil was sampled under trees and bushes. Since soil profiles showed a range of depths, mainly due to present or past tillage operations, data were normalized at 0-25, 25-50 and 50-75 cm calculating the weighted average value for each variable in the three standard control sections to run the model. Soil input data of the three sections are shown in Tables 2-4.

Soil samples were air-dried, and the analyses were made on the <2mm soil fraction after sieving. The soil reaction (pH) was determined in 1:2.5 soil:water suspension by potentiometric method using a pH meter; cation exchange capacity (CEC) with the $BaCl_2$-triethanolamine (pH 8.2) method; particle-size analysis with the wet sieving and sedimentation procedure; total N with the Kjeldahl method, SOC with the Walkley-Black method. Soil bulk density (BD), required to convert SOC concentrations to Mg ha^{-1}, was calculated according to the method proposed by Rawls (1983) and Saxton et al (1986).

2.4 Baseline climate, climate change scenarios and model inputs

The baseline climate was derived from the long-term data series (1985-2006) of Monti station (40° 48' N, 9° 19' E, 296 m a.s.l.), and the climate change scenarios using two Global Climate Models (GCMs): GISS (Hansen et al., 2002), and HadCM3 (Pope et al. 2000). Two emission scenarios based on the Intergovernmental Panel on Climate Change (IPCC, 2007) were chosen: A2, a marked climate change with global warming +3.4 °C by 2100 (uncertainty ranges 2.0-5.4 °C), and B2, a moderate scenario due to mitigation measures, with global warming +2.4 °C (uncertainty ranges 1.4-3.8 °C).

Three time horizons were chosen for climate change projections: 2020, mean climate change for the period 2010‑2039; 2050 for the period 2040‑2069; and 2080 for the period 2070‑2099, providing respectively a very close, an intermediate, and a fully realized climate change scenario (Table 5).

Mean air temperature during winter and summer and annual rainfall required to run CarboSOIL (Muñoz-Rojas et al., 2013) are shown in (Table 6).

2.5 Indicators of model performance

The agreement of model predictions with the measured values of soil organic carbon stocks was tested using the correlation coefficient R^2, and two statistical indicators: the root mean square error (RMSE) and the modelling efficiency (EF):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(O_i - S_i)^2} \qquad \mathrm{EF} = 1 - \frac{\sum_{i=1}^{n}(S_i - O_i)^2}{\sum_{i=1}^{n}(O_i - \overline{O})^2}$$

where O_i and S_i are observed and simulated SOC at i^{th} value, $\bar{O}$ is the mean of the observed data and n is the number of the paired values. The lowest possible value of RMSE is zero, indicating that there is no difference between simulated and observed data. If the model accurately describes the data the RMSE should have approximately the same order of magnitude of the standard deviation (Smith and Smith, 2007). EF compares simulations and observations on an average level, and can range from $-\infty$ to 1, with the best performance at EF=1. Negative values indicate that the simulated values describe the data less well than the mean of the observations.

3. Results and discussion

3.1 Model validation

With reference to the 0-25 cm soil section, R^2, RMSE and EF are 0.977, 8.42, and 0.63 respectively (Fig. 2). In this upper layer, the linear regression coefficients are significant at $p<0.001$ and the standard deviation of the measured values is 14.18, i.e. higher than RMSE.

In the 25-50 cm soil section, R^2, RMSE and EF are 0.990, 5.07, and 0.98 respectively (Fig. 3). The linear regression coefficients are significant at $p<0.001$ and the standard deviation of the measured values is 19.53, i.e. higher than RMSE.

Finally, in the 50-75 cm soil section, R^2, RMSE and EF are 0.762, 5.88, and 0.93 respectively (Fig. 4). In this soil layer, the linear regression coefficients are also significant at $p<0.001$ and the standard deviation of the measured values is also higher than RMSE with a value of 11.09.

Based on the previous considerations, we can affirm that CarboSOIL predictions are fully acceptable for the purpose of this modelling exercise, and can therefore be used for SOC projections under climate change conditions.

3.2 Prediction of SOC changes under climate change

CarboSOIL model predicted an overall increase of SOC stocks in the 2020 climate scenarios in all the soil sections (Fig. 5), with the higher percentage increases in the 50-75 cm section, e.g. 1.1-1.9% in the two vineyards, and 0.8-1.3% in the HC and the PA land use; the smaller increases are observed in the 25-50 cm soil section (0.1-0.8% in the two vineyards, 0-0.3% in HC and PA). Cumulated stocks for the total soil depth (0-75 cm) increased in the order GV (2.3-4.0%) > TV (1.9-3.1%) > PA (1.6-2.6%) > HC (1.2-2.0%) > SN with depth limited to 50 cm (0.4-1.1%) > CO with depth limited to 25 cm (0.3-0.5%).

A SOC decrease is instead expected in the 2050 and 2080 scenarios in the 25-50 cm soil section, more marked in the vineyards in comparison with the other land uses (Fig. 6-7). In particular, SOC decreases in this section were higher in TV (0.2-0.5 and 0.5-1.2% in 2050 and 2080 respectively), and GV (0.4-1.0 and 1.1-2.7%), in comparison with HC (0.1-0.3 and 0.3-0.7%), PA (0.2-0.5 and 0.6-1.4%), and SN (0.1-0.3 and 0.3-0.7%).

Oppositely, slight SOC increases are still expected in the 0-25 cm section (from 0.2 to 1.0% in the two vineyards, and from 0.1 to 0.6% in the other land uses), and to a more extent in the 50-75 cm section, particularly evident in the vineyards. In this section, increases in vineyards are less pronounced in 2050 (1.3-3.3 and 1.7-4.3 % in TV and GV respectively), in comparison with 2080 (3.2-5.5 in TV and 4.1-7.2% in GV). Lower SOC increases are found in HC (0.9-2.4 and 2.1-3.7% in 2050 and 2080) and PA (1.2-3.0 and 2.9-5.0%, again in 2050 and 2080).

A shallow sampling depth is often chosen for reasons of efficiency in monitoring programs, as SOC predominantly accumulates at the surface and in the main rooting zone. Thus, most soils are sampled to a depth of 30 cm or less, and subsoil samplings are not very common (Jandl et al., 2014). However, it has been shown that the SOC pool in the upper mineral soil is not a useful estimator of the total soil C pool as a substantial fraction of this pool can be stored in the subsoil, and this has been shown also for Mediterranean ecosystems (Albaladejo et al., 2013; Chiti et al., 2012; Díaz-Hernández, 2010).

In this context, this research has provided the first estimates of SOC stocks along the soil layers in agro-silvo-pastoral systems typical of a Mediterranean area in Sardinia (Italy) and their trends with climate change. According to the results obtained in the validation process, CarboSOIL model has proved to be consistent and measured values were well correlated with the simulated values.

The results suggest that future climatic scenarios can have a negative effect on SOC stocks in the upper sections of the soil profile, mainly due to a very low increase in the 0-25 cm section and a sharp decrease in the 25-50 cm soil section. The simulated decrease was particularly high by the end of the century in the 2080 time horizon (covering the period 2070-2099), and particularly under the emission scenario A2 with a marked climate change in comparison with the baseline. Moreover, SOC depletion is more marked in the two vineyards and the HC and PA land uses, where soil disturbance is higher in comparison with the cork oak forest (CO) and the semi-natural systems (SN). Also, differences found in the SOC contents along the soil profile and for different land uses might be related to root allocation, which changes across plant species and vegetation types (Yang et al., 2012).

As a fact, increasing temperatures will accelerate SOC decomposition, and decrease photosynthesis rates and crop productivity, with a consequent lower return of crop residues to the soil; it has been reported that climate impacts on croplands and grasslands soils will tend to decrease SOC stocks all over Europe (Smith et al., 2005).

According to our findings, SOC stocks decrease in the top soil layers when rainfall decreases, opposite to the increases in deeper layers. This means that with increasing depth, the relative importance of climatic factors decreases and texture and lithology can become more important in controlling SOC regardless of the land use, in accordance with previous studies in Mediterranean areas of Spain (Albaladejo et al., 2013; Oyonarte at al., 2008).

A range of model projections is considered in this study. We obtained different results of SOC contents associated to different climate predictions which highlight the uncertainty in future climate scenarios. In climate projections, uncertainties can be related to emissions, climatic drivers (e.g., carbon cycle), climate sensitivity and adaptive capacity, among others (Van Vuuren et al., 2011). In areas of complex topography like the Mediterranean region, application of GCMs might result in considerable biases in the prediction of precipitation and temperature (Giorgi and Lionello, 2008). In particular precipitation involves local processes of larger complexity than temperature and projections are usually less robust than those for temperature.

Due to climate change, impacts will be much greater in surface SOC, and the strategies for C sequestration should be focused on subsoil sequestration. In these conditions, carbon sequestration in cropland and managed grassland through appropriate management practices is recommended.

4. Conclusions

The model CarboSOIL has proved its ability to predict SOC stocks at different soil depths, and can be used as a tool for predicting SOC changes under different climate change scenarios in Mediterranean areas which are more vulnerable to temperature increases and rainfall decreases, such as the main islands (e.g. Sardinia) and the Southern Regions of Italy.

Climate change can have a negative impact on SOC stocks in the soil section 25-50 cm, in particular in a long term perspective (2080) and under the marked emission scenario A2, according to our results. Additionally, important decreases of SOC stocks were found in the upper soil sections of the vineyards due to the higher losses in the 25-50 cm soil section.

The methods undertaken in this research may be easily implemented to other Mediterranean areas with accessible information on climate, site, soil and land use. Combining CarboSOIL with spatial databases would allow to evaluate regional SOC stocks and sequestration potential to support land management strategies and policies.

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Table 1

CarboSOIL input variables, units, sources and references

Variable type	Variable name	Code	Unit	Source and reference
Dependent variable	Soil Organic C	SOCC	Mg/ha	University of Sassari Francaviglia et al. (2012;2014)
Climate	Total precipitation	PRPT	mm	CRA elaborations from baseline data and GCMs
	Winter Temperature	TDJF	^{o}C	
	Summer Temperature	TJJA	^{o}C	
Site	Elevation	ELEV	m	University of Sassari
	Slope	SLOP	%	
	Drainage	DRAI	-	
	Soil Erosion	SERO	-	
Soil	Nitrogen	NITRO	%	Field surveys and lab analyses Francaviglia et al. (2012 ;2014)
	pH	PHWA	-	
	Cation Exchange Capacity	CEXC	cmol$_{(+)}$ kg^{-1}	
	Sand	SAND	%	
	Clay	CLAY	%	
	Bulk density	BULK	g cm^{-3}	
	Field capacity	FCAP	%	
Land use	Land use/land cover	LULC	-	Field surveys

Table 2

Input parameters of soil section 0-25 (mean ±SD).

Land use	Sand	Silt	Clay	pH	CEC	FC	Total N	SOC
	%				cmol$_{(+)}$ kg^{-1}	%		
TV	82.5±3.5	5.9±4.3	11.6±1.1	5.1±0.1	12.6±2.6	9.1±1.2	0.09±0.01	1.18±0.14
GV	79.6±0.3	8.9±1.4	11.5±1.4	6.2±0.4	15.7±1.4	9.9±1.3	0.09±0.00	1.20±0.38
HC	73.5±0.3	13.7±0.4	12.8±0.7	5.6±0.4	15.4±2.1	13.3±1.7	0.13±0.01	2.00±0.57
PA	73.1±1.2	13.4±0.6	13.5±0.8	5.5±0.4	17.2±3.7	13.0±0.9	0.20±0.02	1.84±0.30
CO	78.1±2.9	10.5±2.6	11.4±0.3	5.6±0.2	16.6±3.2	12.1±1.3	0.17±0.02	2.06±0.34
SN	79.9±3.1	10.9±3.6	9.2±2.3	6.0±0.3	17.8±6.2	10.2±1.2	0.10±0.03	1.63±0.29

Table 3

Input parameters of soil section 25-50 (mean ±SD).

Land use	Sand	Silt	Clay	pH	CEC	FC	Total N	SOC
	%				cmol$_{(+)}$ kg^{-1}	%		
TV	84.3±3.4	4.6±3.6	11.1±0.6	5.3±0.3	14.6±4.1	8.9±1.3	0.07±0.04	0.99±0.59
GV	84.1±4.7	7.3±1.8	8.6±2.9	6.2±0.8	15.4±2.7	7.4±2.9	0.05±0.03	0.66±0.62
HC	73.7±7.9	14.4±7.5	11.9±0.9	5.8±0.3	15.2±1.3	11.6±1.8	0.09±0.02	1.43±0.36
PA	76.1±2.7	11.2±1.7	12.7±2.4	5.6±0.4	13.2±1.9	10.1±1.2	0.08±0.03	0.88±0.39
CO*	-	-	-	-	-	-	-	-
SN	82.7±2.5	8.0±1.8	9.3±1.9	6.2±0.3	18.7±8.0	9.5±1.1	0.07±0.02	1.48±0.35

* depth limited by rock

Table 4

Input parameters of soil section 50-75 (mean ±SD).

Land use	Sand	Silt	Clay	pH	CEC	FC	Total N	SOC
	%				$cmol_{(+)}$ kg^{-1}	%		
TV	86.1±1.5	3.7±2.6	10.2±1.5	5.6±0.6	17.6±5.4	7.8±2.3	0.07±0.04	0.79±0.77
GV	89.5±2.0	4.1±2.9	6.4±0.9	6.3±0.5	15.5±3.0	5.0±0.4	0.05±0.03	0.62±0.58
HC	78.3±7.3	11.2±7.4	10.5±1.1	6.2±0.2	14.2±2.6	8.6±2.6	0.04±0.02	0.62±0.13
PA	77.8±4.1	9.1±3.5	13.1±5.0	5.6±0.3	12.5±2.9	9.3±2.9	0.04±0.01	0.53±0.25
CO*	-	-	-	-	-	-	-	-
SN*	-	-	-	-	-	-	-	-

* depth limited by rock

Table 5

Changes in the mean annual temperature and rainfall compared with the baseline climate.

Emission scenario	Time horizon	Temperature (+°C)		Rainfall (−mm)	
		GISS	HadCM3	GISS	HadCM3
A2	2020	0.5	0.7	39.9	43.3
	2050	1.4	1.9	70.1	28.6
	2080	3.1	3.5	108.9	129.4
B2	2020	0.6	0.7	75.0	39.0
	2050	1.0	1.4	108.6	65.4
	2080	2.0	2.2	131.2	52.7

Table 6

Climate inputs for the model.

Emission scenario	Time horizon	Winter temperature (C°)		Summer temperature (°C)		Rainfall (mm)	
		GISS	HadCM3	GISS	HadCM3	GISS	HadCM3
A2	2020	8.5	8.6	23.3	23.6	623.6	620.2
	2050	9.1	9.7	24.6	25.3	593.4	634.9
	2080	10.2	10.9	26.7	27.3	554.6	534.1
B2	2020	8.7	8.6	23.4	23.8	588.5	624.5
	2050	8.5	9.3	24.2	24.6	554.9	598.1
	2080	9.6	9.8	25.3	25.7	532.3	610.8
Baseline climate		7.8		23.0		663.5	

Fig. 1. Location of the study area (Sardinia, Italy).

Fig. 2. Regression between predicted and measured SOC stocks for soil section 0-25 cm.

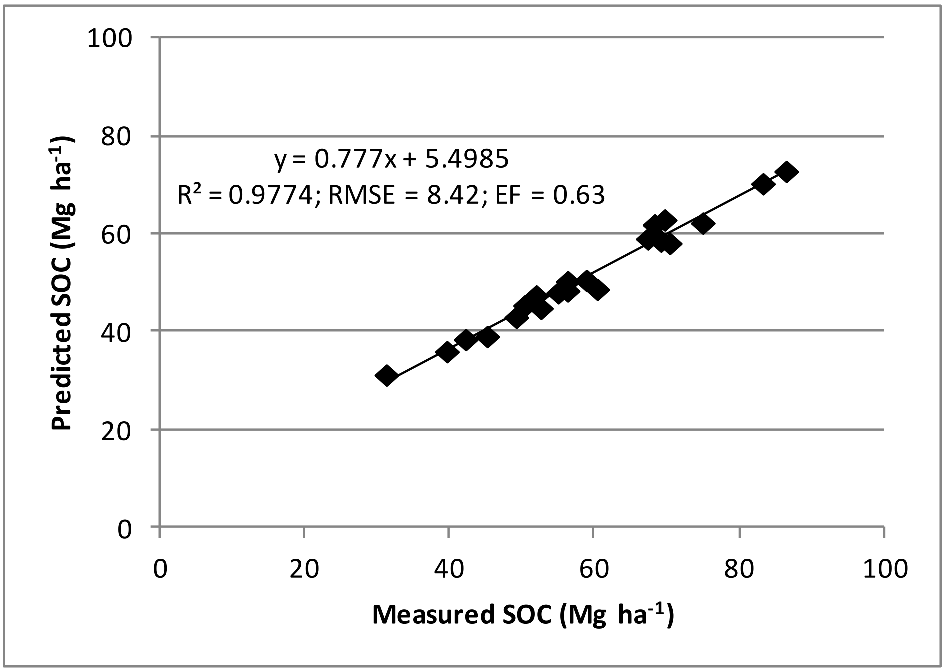
Fig. 3. Regression between predicted and measured SOC stocks for soil section 25-50 cm.

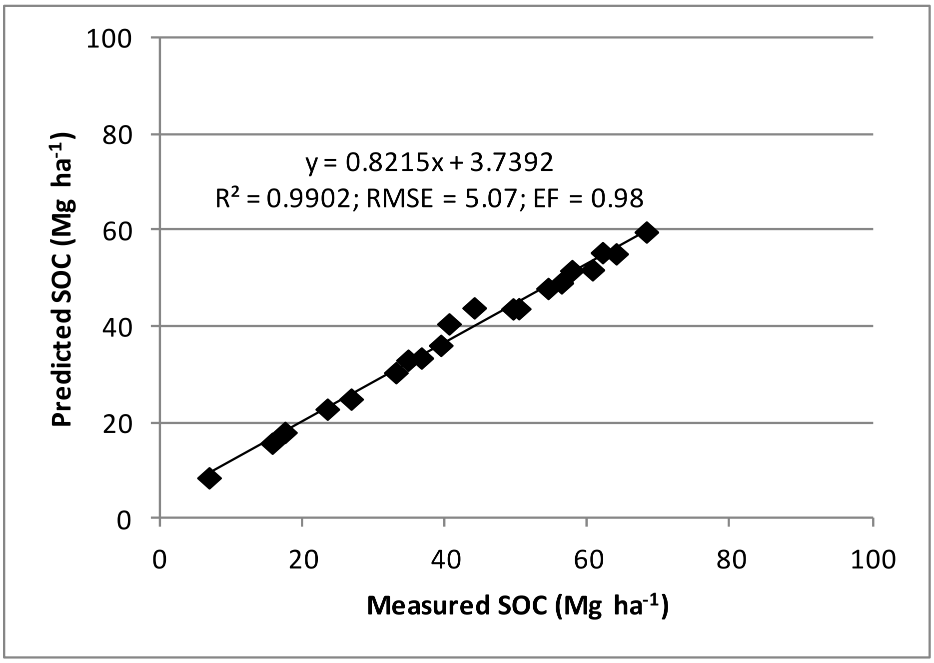
Fig. 4. Regression between predicted and measured SOC stocks for soil section 50-75 cm.

Fig. 5. Soil organic C stocks changes in 2020 under emission scenarios A2 and B2 for each land use at different soil depths (0–25, 25–50, 50–75 cm).

Fig. 6. Soil organic C stocks changes in 2050 under emission scenarios A2 and B2 for each land use at different soil depths (0–25, 25–50, 50–75 cm).

Fig 7. Soil organic C stocks changes in 2080 under emission scenarios A2 and B2 for each land use at different soil depths (0–25, 25–50, 50–75 cm).


100
80
60
40
20
0
0
20
40
60
80
100
Predicted SOC (Mg ha-1)
Measured SOC (Mg ha-1)
y = 0.777x + 5.4985
R² = 0.9774; RMSE = 8.42; EF = 0.63


y = 0.8215x + 3.7392
R² = 0.9902; RMSE = 5.07; EF = 0.98
Predicted SOC (Mg ha-1)
Measured SOC (Mg ha-1)
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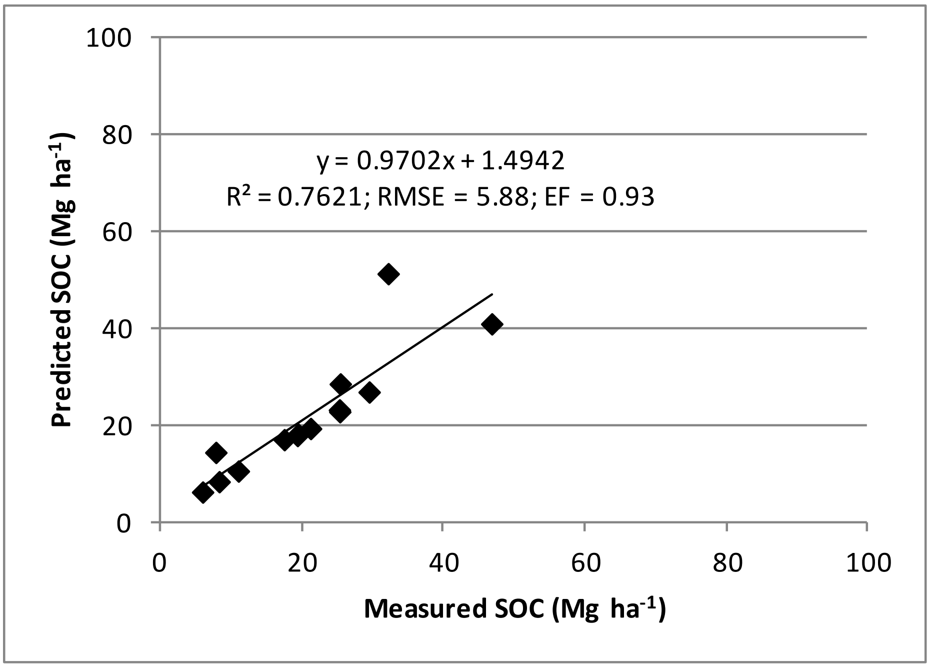
20
40
60
80
100
0
20
40
60
80
100


y = 0.9702x + 1.4942
R² = 0.7621; RMSE = 5.88; EF = 0.93
Predicted SOC (Mg ha-1)
Measured SOC (Mg ha-1)
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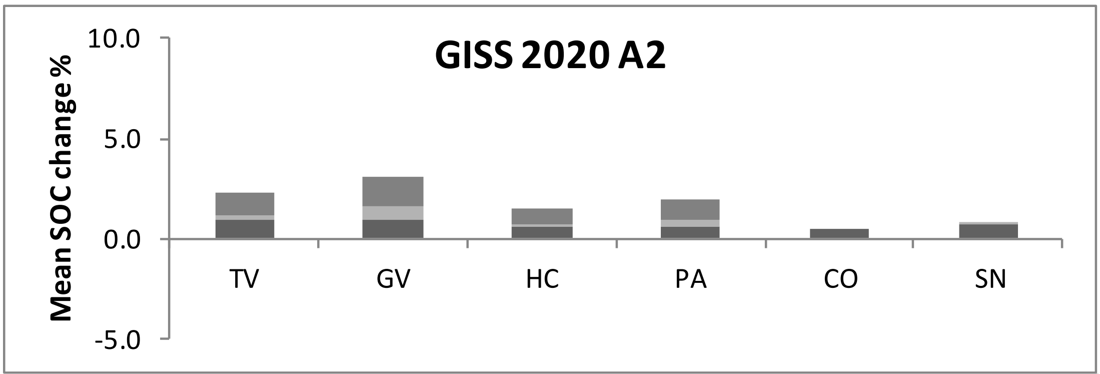
40
60
80
100
0
20
40
60
80
100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Mean SOC change %
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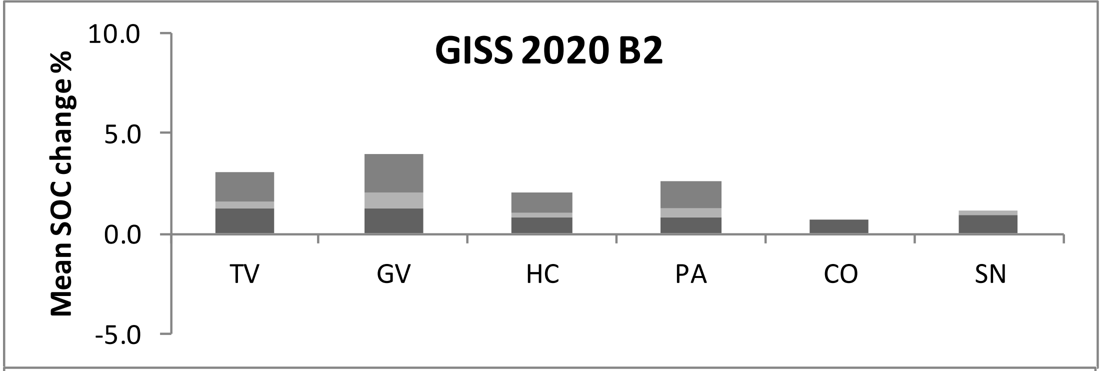
5.0
0.0
-5.0
TV
GV
HC
PA
CO
SN


GISS 2020 B2
Mean SOC change %
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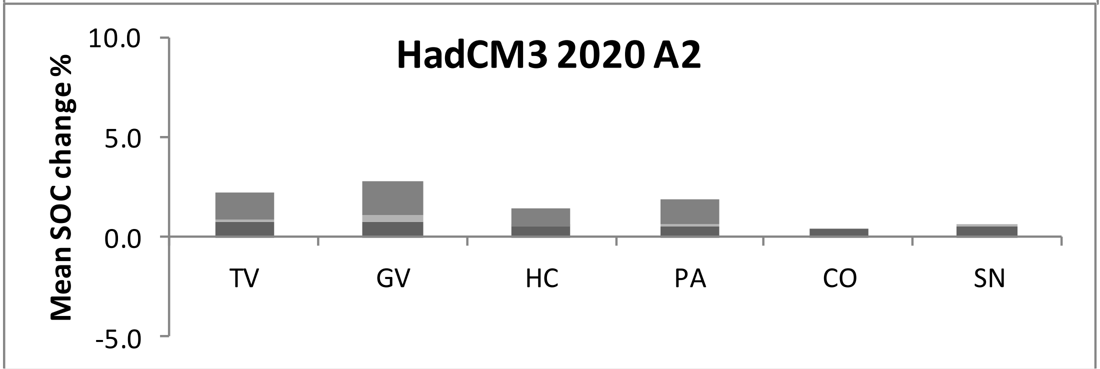
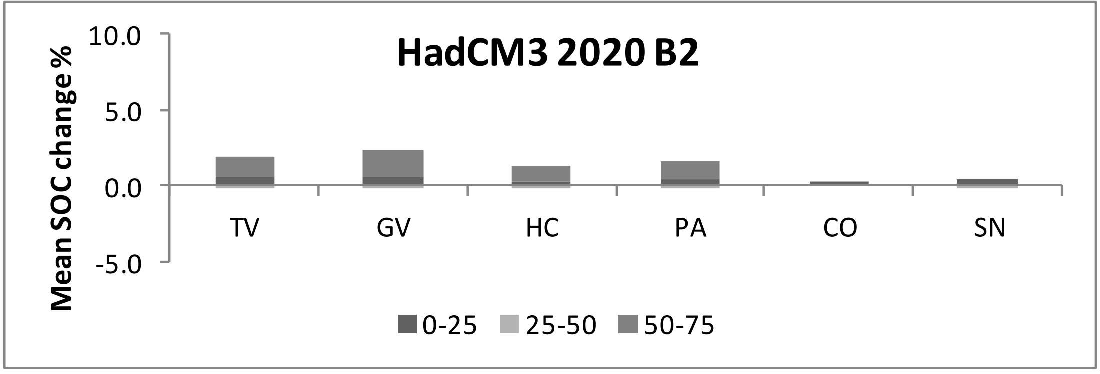
5.0
0.0
-5.0
TV
GV
HC
PA
CO
SN


HadCM3 2020 A2
Mean SOC change %
10.0
5.0
0.0
-5.0
TV
GV
HC
PA
CO
SN


HadCM3 2020 B2
Mean SOC change %
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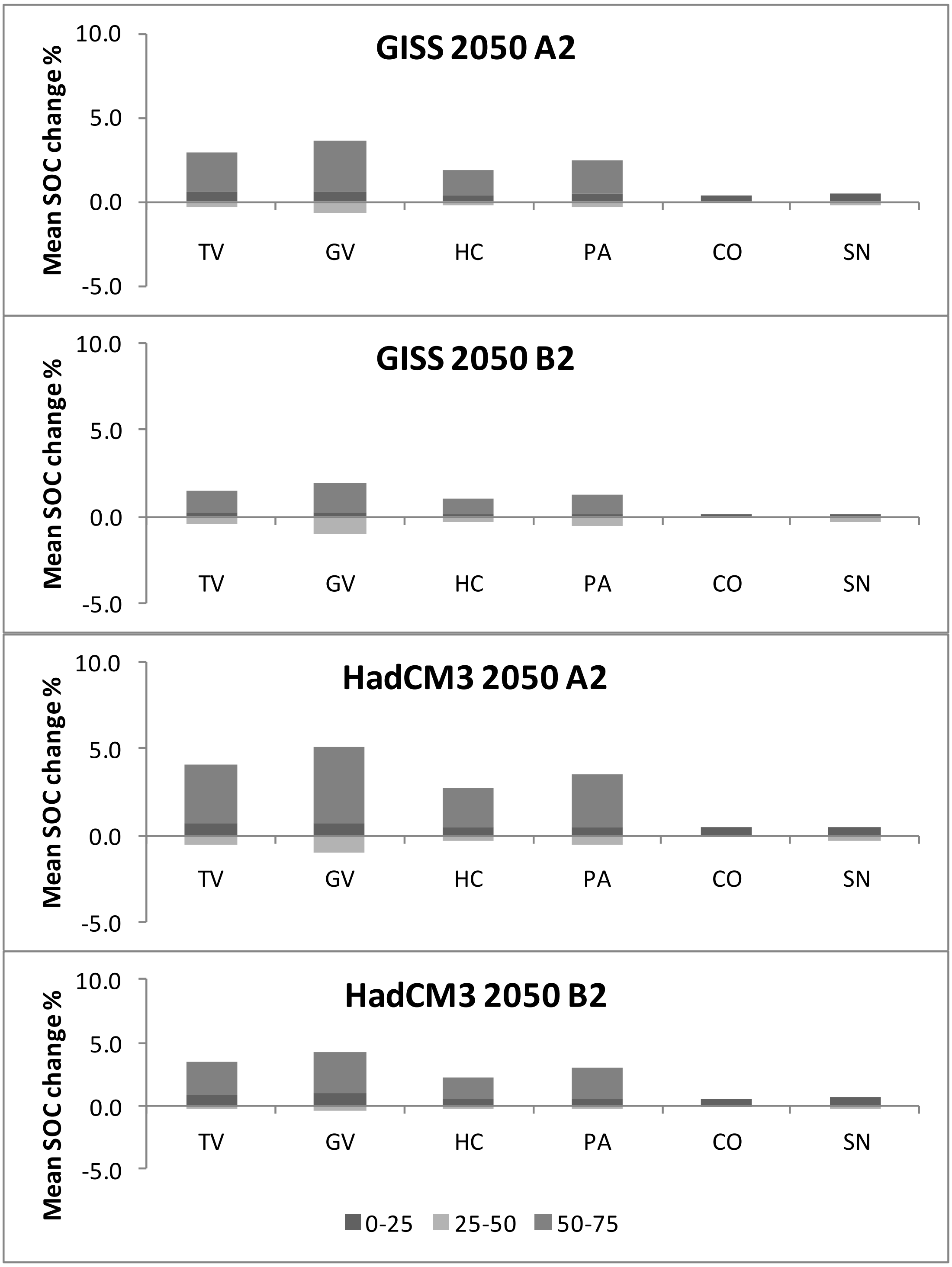
5.0
0.0
-5.0
TV
GV
HC
PA
CO
SN
0-25
25-50
50-75


GISS 2050 A2
GISS 2050 B2
HadCM3 2050 A2
HadCM3 2050 B2
Mean SOC change %
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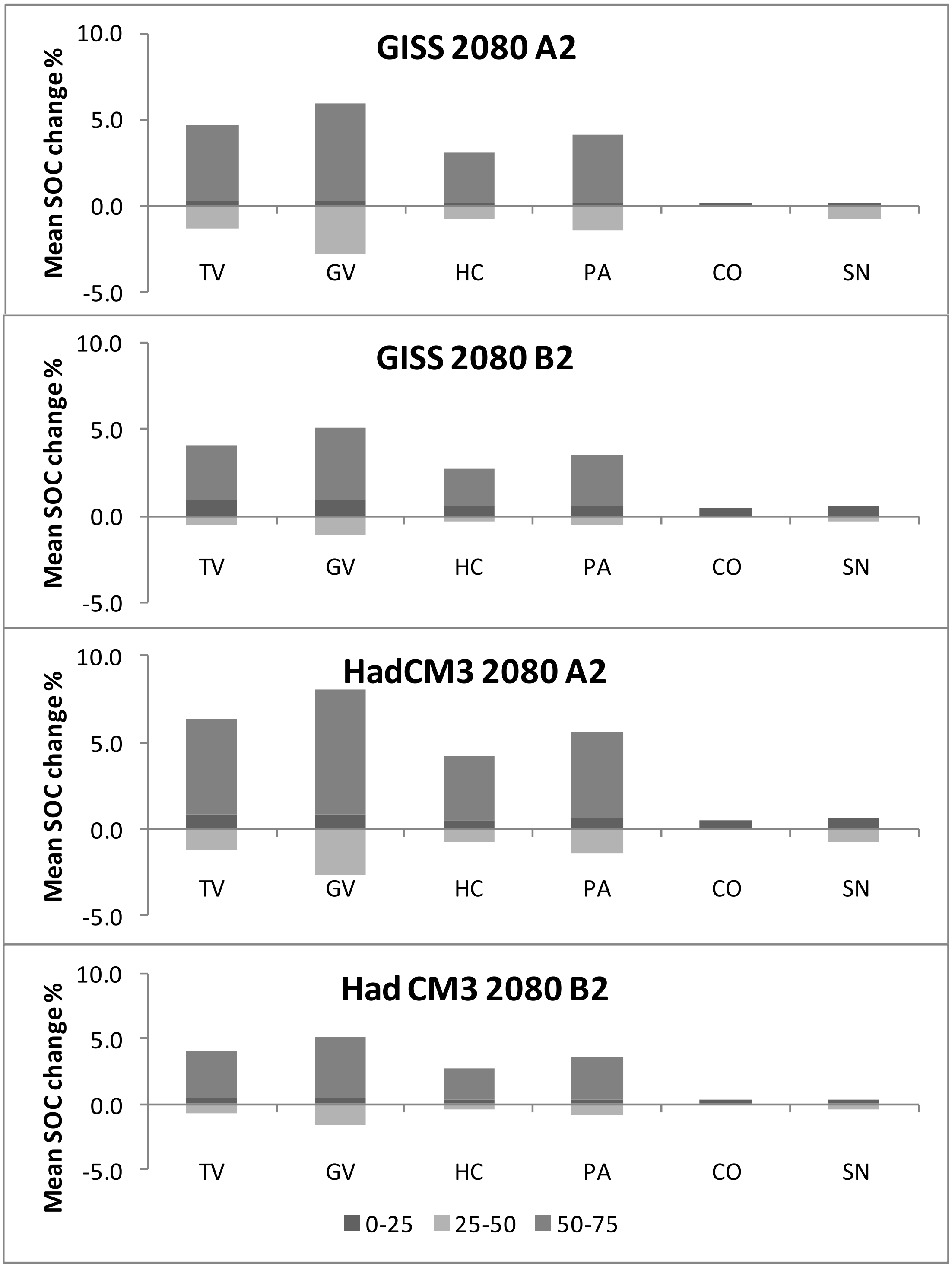
5.0
0.0
-5.0
TV
GV
HC
PA
CO
SN
0-25
25-50
50-75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GISS 2080 B2
HadCM3 2080 A2
Had CM3 2080 B2
Mean SOC change %
10.0
5.0
0.0
-5.0
TV
GV
HC
PA
CO
SN
0-25
25-50
50-75