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A Multipurpose Soil Inorganic Carbon Prediction Model

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Abstract: There is a lack of models to predict soil inorganic carbon (SIC) which are not only multipurpose, but can predict SIC in a variety of soils and materials. The importance of estimating SIC stocks is due to the large contribution they make towards total carbon in some soils. This paper proposes such a model which aims to account for the variance and geographical range of soils. As an example, one such use is the accurate prediction of passive SIC sequestration rates as this is currently a complex challenge, mainly due to environmental effects such as water, temperature and atmospheric CO_2 concentrations. The model is process based, taking into account environmental, physical and biological factors which can be scaled up to the appropriate levels of analysis. There is therefore need for a multipurpose model that can be used by a wide range of users, and at several scales. Recent evidence from brownfield sites featuring urban soils indicates potential for carbon capture through conversion of C to $CaCO_3$. A component of this proposed model therefore consists of a sub-system defined as CASPER (Carbon Absorption Soil Prediction for Engineered Regions). For the purpose of this framework, this component aims in the future to model data from the results of a wider UK funded research project known as SUCCESS (Sustainable Urban Carbon Capture: Engineering Soils for Climate Change).

***Keywords**:* Soil Inorganic Carbon; Carbon Capture; Soil Science; Environmental Forecasting

1 INTRODUCTION

1.1 Background

Soil inorganic carbon (SIC) stocks are not measured by many national and continental-scale soil monitoring networks (Marchant et al., 2015; Rawlins et al., 2011). Despite being large in certain cases reserves of inorganic C have been estimated to be around 730-980 Pg by Schlesinger (1982) and 720 Pg of C by Sombroek et al (1990). The SIC pool can be classified as lithogenic inorganic C (LIC) and pedogenic inorganic C (PIC) with the former inherited from parent material of the soil, with no temporal change in soil inorganic C content other than dilution. The latter is formed through the precipitation of newly-formed carbonate material (Wu et al., 2009). A lack of inorganic carbon models exist that are capable of capturing the effects of the many physical, chemical and biological processes within soils. This is due in part to a lack of analysis and observation of inorganic carbon precipitation in soil monitoring networks (Marchant et al., 2015). Examples include the Soil Profile Analytical Database of Europe (Breuning-Madsen & Jones, 1995). There is therefore a further need to monitor SIC where it supports functional ecosystem properties, such as carbon sequestration. According to the ENVASSO European Survey (Arrouays et al., 2008) SIC was monitored in only six of the 27 members of the European Community.

Instead, SMNs tend to focus on soil properties that are related to soil fertility and are expected to evolve rapidly (e.g. pH, organic carbon and soil nutrients) or on soil properties that are of environmental concern (e.g. heavy metals and organic pollutants). While SIC studies currently exist, the findings are isolated, and the results are not currently presented in a way that can be recorded and normalised for applications attempting to predict inorganic carbon precipitation. Therefore a participatory approach to collecting inorganic carbon data needs to be explored. Advanced innovative technologies such as smart phones and touch-screen tablets are emerging as an effective mechanism for participatory engagement with researchers, decision makers and stakeholders. Use of technology such as mobile phones has been facilitated in part by research that is motivated by undertaking a more 'participatory approach', where the objectives include enhancing stakeholder and community engagement and the elicitation of information from the 'knowledge domain'. It should therefore be noted that the proposed model aims to be incorporated into an app using the JAVA programming language which aims to allow soil scientists, environmental consultants and governmental officials to upload results with the aim of normalising findings from environmental variables to more accurately determine inorganic carbon precipitation, with the goal of improving prediction accuracy of the model.

1.2 Functions of Inorganic Carbon

Recent studies of SIC stocks have revealed that certain soils, particularly urban soils and those containing basaltic quarry fines, possess a rapid passive carbon capture function, and act as sinks of atmospheric CO_2, (Schmidt et al., 2011). CO_2 partitions into soil pore waters as dissolved carbonate, and precipitates by combining with Ca derived from portlandite ($Ca(OH)_2$) and weathered cementderived calcium silicates, from materials such as crushed concrete generated by the demolition process (Renforth et al., 2011a; Washbourne et al., 2012). Therefore such soils have a large potential to store C and the addition of construction and demolition (C&D) waste, fly ashes, iron and steel slag etc. may enhance C capture and storage in the urban soils (Morales-Flórez et al., 2011; Renforth et al., 2011a; Renforth et al., 2009; Renforth et al., 2011b). Furthermore, the value of materials which may otherwise be regarded as 'wastes' is increased. According to Washbourne et al (2015), SIC rates equivalent to removal of up to 85t/ha/yr CO_2 have been recorded at the former site of Newcastle Brewery, situated within Newcastle Upon Tyne, UK. There is also potential for carbon capture using basaltic quarry fines, a by-product produced during the crushing process in the manufacture of construction aggregates (Manning et al., 2013). Recently, work carried out by the SUCCESS (Sustainable Urban Carbon Capture: Engineering Soils for Climate change) project (2014-2017) aims to determine which mixture of soil material performs best at absorbing CO_2 based predominantly on SIC (Jorat et al., 2015a; Jorat et al., 2015b; Kolosz et al., 2015).

Other functions of SIC include the dissolution of carbonate, which acts as the dominant buffering mechanism that inhibits acidification when nitrogen fertilizers are used (Marchant et al., 2015). Therefore SIC can provide other useful benefits. There are therefore strong arguments to incorporate SIC into soil monitoring schemes. As there is a need to track the overall soil/ecosystem potential to mitigate/exacerbate climate change, this paper proposes a multipurpose inorganic carbon prediction model, that also accounts for biological properties such as Soil Organic Carbon (SOC), by utilising existing models such as the Rothamsted Carbon Model (RothC) which is designed to predict the turnover of SOC (Coleman & Jenkinson, 1996).

1.3 Previous Studies of Inorganic Carbon Prediction in Soils

There have been very limited attempts to model IC concentrations and stocks, with only statistical models so far, but a dynamic first-principles models is required if it is to be of general use for the identified applications. Rawlins (2011) attempted to predict IC precipitation by creating linear regression models (R^2 between 0.8 and 0.88) to estimate IC in topsoil based on total Ca and Al concentrations for soils over two groups of primary, carbonate-bearing parent materials across parts of southern and eastern England. By applying the regression models to geochemical survey data across the entire area (18 165 km^2), they estimated IC concentrations on a regular 500-m grid by ordinary kriging. Using bulk density data from across the region, the total IC stock of soil (0–30 cm depth) in this area was estimated to be 186 MtC. This represents 15.5 and 5.5% of the estimated total soil carbon stock (OC plus IC) across England and the UK, respectively. Soil geochemical data could be useful for estimating primary IC stocks in other parts of the world. Marchant et al (2015) attempted to predict the total inorganic carbon level of France. Statistical methods were used to calculate unbiased estimates of the mean SIC concentration and the data was normalised using non parametric transformation. Results indicated that the total SIC contribution was 1070 ± 61 Tg, ca one-third of the corresponding organic carbon stocks. Of particular note about this study was that the levels of SIC were related to the geology underlying the samples. This paper aims to provide a model framework for attempting to predict the precipitation of inorganic carbon within multiple types of soil substrate, and aims to be updated as new results become available from academic and industrial stakeholders where available. The following sections illustrate the existing methods, the proposed method for estimating SIC stocks, and finally, the conclusions and recommendations.

2 METHODS

In order to model the environmental, biological and physical factors controlling SIC, a variety of methods were used. Roth C and CENTURY are two of the most widely used dynamic soil carbon models for estimating soil carbon turnover worldwide (Liski et al., 2005). These models operate on a monthly time step and require soil texture and weather variables as their major input data.

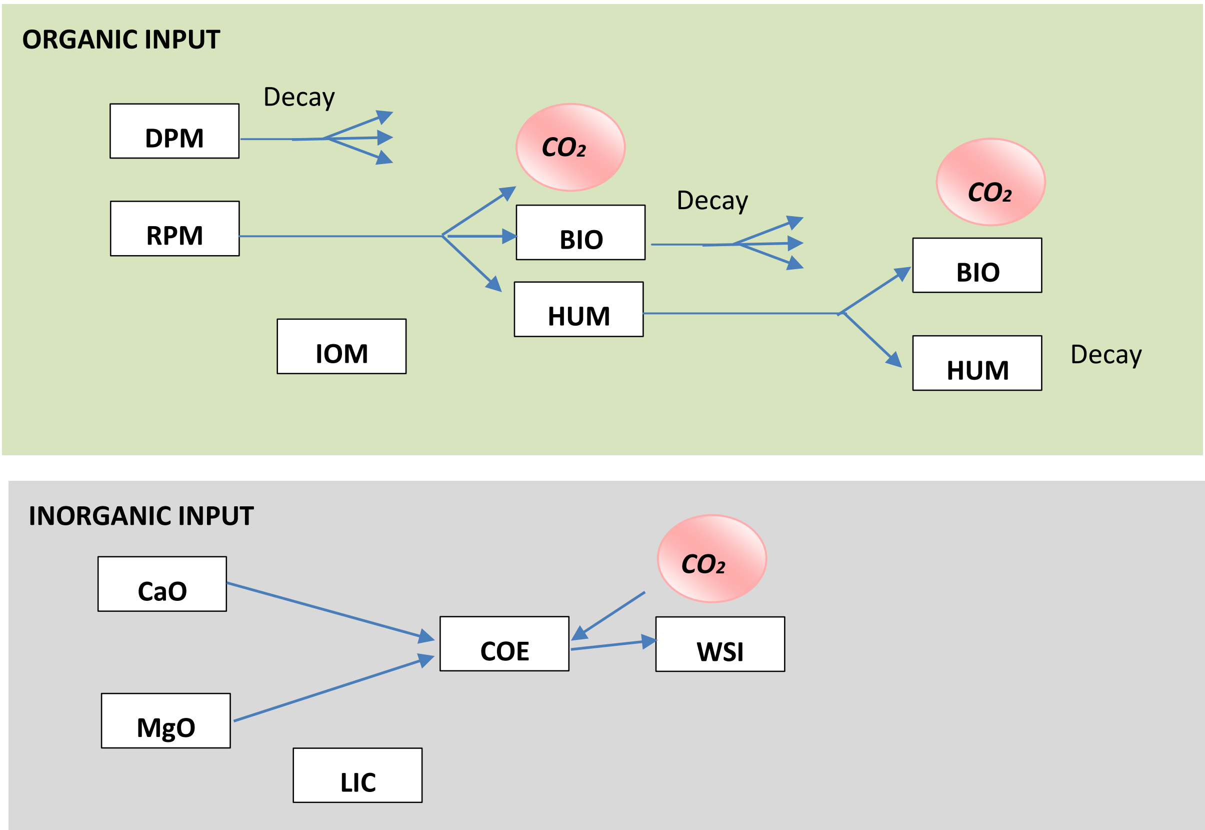

Figure 1: Roth C organic components (top) and proposed inorganic components (bottom)

1.4 Roth C

Some elements from Roth C have been extracted in order to estimate organic carbon absorption (Coleman & Jenkinson, 1996). In addition to including a small amount of Inert Organic Matter (IOM) four active components from Roth C include Decomposable Plant Material (DPM), Resistant Plant Material (RPM), Microbial Biomass (BIO) and Humified Organic Matter (HUM). Inorganic elements have been added to the proposed model in order to illustrate the differences. The key decisions that determined the parts of ROTH C that were retained were based upon elements affecting CO_2 uptake as opposed to the loss of CO_2 into the atmosphere.

Table 1: Criteria for Total Carbon Prediction

Criteria	Value	Description	Dataset dependence
Monthly rainfall	mm	In order to determine the rate of mineral weathering, it is necessary to assess the monthly rainfall, From this, the level of bicarbonate dissolution can be estimated which in turn can determine amount of CO_2 uptake.	Localised to particular region
Monthly open pan evaporation	mm	Rainfall and open-pan evaporation are used to calculate topsoil moisture deficit (TSMD), as it is easier to do this than obtain monthly measurements of the actual topsoil water deficit.	Muller (1982)
Clay content of the soil	%	Clay content is used to calculate how much plant available water the topsoil can hold; it also affects the way organic matter decomposes.	Localised to particular region
DPM/RPM Ratio	<0-1>	An estimate of the decomposability of the incoming plant material	Roth C
Average monthly mean air temperature	Cº	Air temperature is used rather than soil temperature because it is more easily obtainable for most sites. Temperature effects the rate of reaction in both organic and inorganic chemical processes.	Localised to particular region
Soil Cover	Cover Material	Is the soil bare or vegetated in a given month?	Roth C
Monthly input of plant residue	t C ha^{-1}	The plant residue input is the amount of carbon that is put into the soil per month. This input is rarely known, therefore models such as Roth C operate in inverse mode i.e. generating input from known soil, site and weather data.	Roth C
Depth of soil layer sampled	cm	Linked to average monthly temperature, although the variations are usually ±1Cº for the first 20 cm.	Linked to average monthly temperature
Quantity of calcium/magnesium silicates	g/ha	Calcium and magnesium silicates form part of the carbon capture function, acting as feedstocks.	CASPER
Known CO_2 absorption efficiency	0-1/%	The rate of successful transition of CO_2 to calcium carbonate ($CaCO_3$). This criterion may also be dependent on background CO_2 although little data exists to confirm this.	CASPER
Carbonate saturation period	years	The total lifespan of the carbon capture function within the material.	CASPER
Particle size	µm-mm	The particle size of the soil.	CASPER
Ambient background CO2 Intensity	Ppm	Ambient levels of background CO_2 intensity at the site	CASPER

The inorganic components consist of the current level of calcium and magnesium silicates (CaO) and (MgO) respectively, the weathering efficiency factor of silicate conversion to calcium carbonate ($CaCO_3$) and the by-product of this conversion in the form of waste silicic acids (WSI) of the chemical formula H_4SiO_4. A small amount of Lithogenic Inorganic Carbon (LIC) will also exist within the soil. The carbonation process is important in natural soils (Nettleton, 1991) but its extent in artificial soils has only been recently appreciated (Renforth & Manning, 2011). A simplified version of the carbonation reaction for artificial calcium silicates is given in Reaction 1.

$$CaSiO_3 + CO_2 + 2H_2O \rightarrow CaCO_3 + H_4SiO_4 \quad (1)$$

2.2 CENTURY

CENTURY was originally developed for grassland soil types and is a model of terrestrial biogeochemistry (Metherell, 1993; Parton et al., 1987; Parton et al., 1993). It is based upon relationships between climate, human management (fire, grazing), soil properties, plant productivity and decomposition. The results show that soil C and N levels can be simulated to within +25% of the observed values (100 and 75% of the time, respectively) for a diverse set of soils.

3 PROPOSED METHOD AND POINTS TO CONSIDER FOR THE DESIGN OF A SOIL INORGANIC CARBON MODEL

1.5 Data collection

In order for the model to accurately predict inorganic carbon as well as total carbon potential, a number of specific criteria are required. Such data can be acquired from scientific studies, existing models and the local public domain. Monthly rainfall affects primarily both inorganic and organic carbon flows into the soil. According to the Roth C guidance document, if open-pan evaporation is not available, monthly potential evapotranspiration can be calculated with adequate accuracy from Müller's (1982) collection of meteorological data for sites around the world. The criteria that are required to be used in conjunction with the model are listed in Table 1.

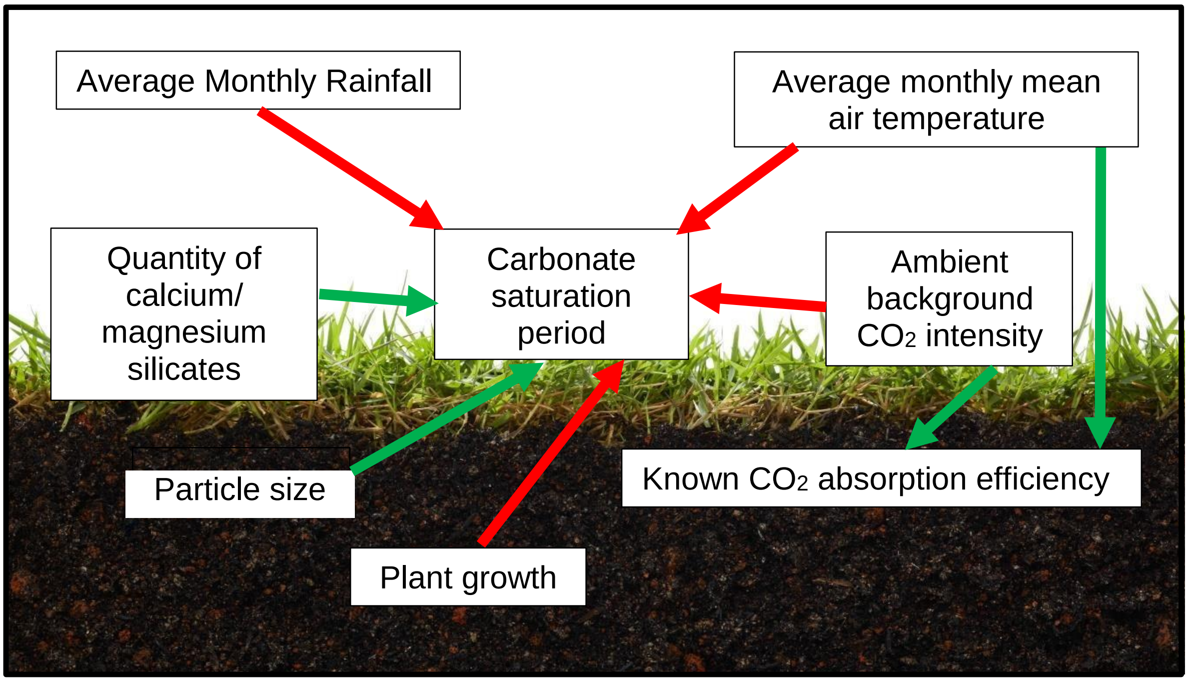

Figure 2: Relationships of the proposed inorganic soil carbon model

3.2 Assessing key relationships for predicting inorganic carbon precipitation

Predicting inorganic carbon relies on a number of distinct criteria. For example, the conversion process of CO_2 to $CaCO_3$ is dependent on surface area, concentration of suitable chemicals and average monthly rainfall where CO_2 is dissolved in the soil solution, reacting with calcium and magnesium silicates. Average monthly mean temperature may also have an impact on the rate of C absorption, as evidenced by Kirchofer et al (2012), however, the variation in temperature would need to be substantial for its impact to be noticed, i.e. way beyond the natural background ranges. Particle size also drives the aeration i.e. the amount of CO_2 that is filtered into the substrate and indicates roughly the amount of space between the soil matter where calcium carbonate may precipitate which in turn is dependent on the quantity of calcium and magnesium silicates. Ambient background CO_2 intensity may have a direct influence on the known CO_2 absorption efficiency. For example, it is known that plant growth is affected by elevated CO_2 concentrations with an even greater effect at tropical temperatures (Drake et al., 1997; Kimball et al., 1993; Nowak et al., 2004). The effect of elevated levels of CO_2 combined with rainfall and temperature may cause rapid acceleration of the absorption efficiency, and although this can be recreated in a controlled lab based setting for 'active' carbon capture (Kirchofer et al., 2012) it is at this time difficult to determine how CO_2 fluctuations will affect the rate of carbon capture in a natural environment although soil partial pressures of CO_2 can be very high.

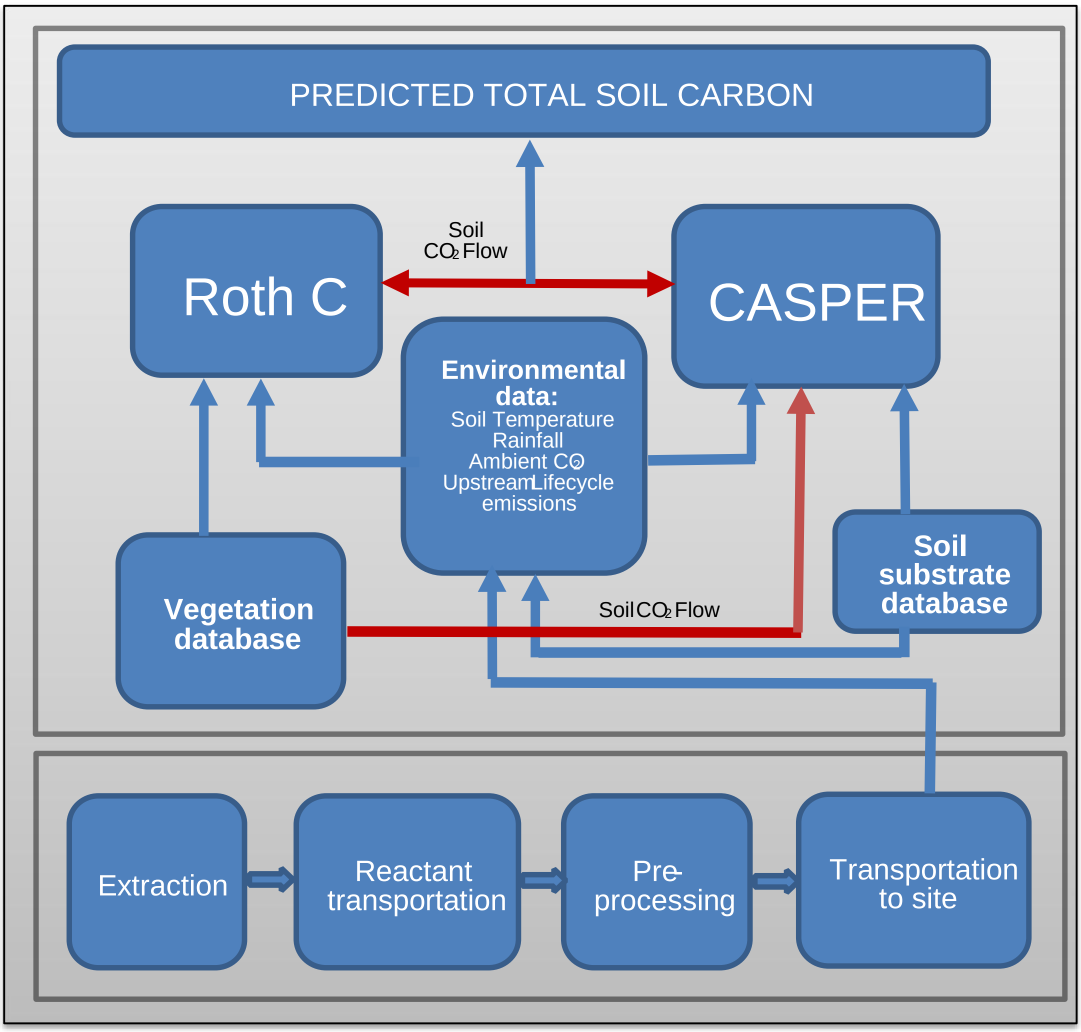

Figure 3: Schematic of the proposed technical components

1.6 Developing the Model Framework within Life-cycle Assessment

The model contains a number of technical components that are designed to interact with two subsystems: The organic soil carbon system (Roth C) and the inorganic soil carbon system (CASPER) which is designed to emulate the systems required to determine total soil carbon have been integrated into this framework (Figure 3). The environmental data is shared between the organic and inorganic soil carbon sub-systems. The soil substrate database contains all necessary information relating to soil properties. This includes but not limited to substrate type, clay content, and calcium and magnesium silicate content. The vegetation database concerns ecological specifications although the identity of the necessary elements are being assessed via experimental work.

2 CONCLUSIONS AND DISCUSSION

The paper has proposed the general outline of a multipurpose inorganic soil carbon prediction model. While aiming to primarily assess inorganic carbon precipitation, the model is designed to take into account soil organic carbon in order to estimate total carbon soil absorption as part of a wider life cycle assessment approach. The model requires a selected number of criteria in order to function successfully. This data is becoming more widely available, particularly through several research projects including SUCCESS, therefore proper participation of various stakeholders through an appropriate mobile app will allow the model to become more refined, as time goes on.

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