A review on the global soil property maps for Earth system model

Yongjiu Dai[1*], Wei Shangguan[1*], Dagang Wang[2], Nan Wei[1], Qinchuan Xin[2], Hua Yuan[1], Shupeng Zhang[1], Shaofeng Liu[1], Xingji Lu[1], Fapeng Yan[3]

[1] Guangdong Province Key Laboratory for Climate Change and Natural Disaster Studies, School of Atmospheric Sciences, Sun Yat-sen University, Guangzhou, China.
[2]School of Geography and Planning, Sun Yat-sen University, Guangzhou, China.
[3]College of Global Change and Earth System Science, Beijing Normal University, Beijing, China

Correspondence to: Yongjiu Dai(daiyj6@mail.sysu.edu.cn) and Wei Shangguan (shgwei@mail.sysu.edu.cn)

Abstract. Soil is an important regulator of Earth system processes, but remains one of the least well-described data layers in Earth System Models (ESMs). We reviewed global soil property maps from the perspective of ESMs, including soil physical and, chemical and biological properties, which can also offer insights to soil data developers. These soil datasets provide model inputs, initial variables and benchmark datasets. For modeling use, the dataset should be geographically continuous, scalable and with uncertainty estimates. The popular soil datasets used in ESMs are often based on limited soil profiles and coarse resolution soil type maps with various uncertainty sources. Updated and comprehensive soil information needs to be incorporated in ESMs. New generation soil datasets derived by digital soil mapping with abundant, harmonized and quality controlled soil observations and environmental covariates are preferred to those by the linkage method (i.e. taxotransfer rule-based method) for ESMs. Soilgrids has the highest accuracy and resolution among the global soil datasets at the time, while other recently developed datasets are useful compliments. Because there is no universal pedotransfer function, an ensemble of them may be more suitable to provide derived soil properties to ESMs. Aggregation and upscaling of soil data are needed for model use but can be avoid by taking a subgrid method in ESMs at the cost of increases in model complexity. Producing soil property maps in time series is still challenging. Uncertainty of soil data needs to be estimated and incorporated in ESMs.

1 Introduction

Soil or pedosphere is a key component of Earth system, and plays an important role in the water, energy and carbon balances and other biogeochemical processes. An accurate description of soil properties is essential in advancing the modeling capabilities of Earth System Models (ESMs) to predict land surface processes at the global and regional scales (Luo et al., 2016). Soil information is required by the land surface models (LSMs), which is a component of ESMs. With the help of computer-based geographic systems, many researchers have produced geographical databases to organize and harmonize large amount of soil information generated from soil surveys during the last decades (Batjes, 2017; Hengl et al., 2017). However, soil dataset used in ESMs is not well updated nor well utilized yet (Sanchez et al., 2009; FAO/IIASA/ISRIC/ISS-CAS/JRC, 2012). The popular soil datasets used in ESMs are outdated and with limited accuracy. Some soil properties such as gravel (or coarse fragment) and depth to bedrock are not utilized in most ESMs. Meanwhile, it is needed to change ESMs' schemes and structure to represent soil processes more realistic in utilizing new soil information (Brunke et al., 2016; Luo et al., 2016; Oleson et al., 2010). For example, Brunke et al., (2016) incorporated the depth to bedrock data in a land surface model using variable soil layers and instead of the previous constant depth. Better soil information with high resolution and better representation of soil in models have improved and will improve the performance in simulating the Earth system (eg. Livneh et al., 2015; Dy and Fung, 2016; Kearney and Maino, 2018).

ESMs require detailed information on the soil physical, chemical and biological properties. Site observations (called soil profiles) from soil surveys include soil properties such as soil depth, soil texture (sand, silt and clay fractions), organic matter, coarse fragments, bulk density, soil colour, soil nutrients (carbon (C), nitrogen (N), phosphorus (P), potassium (K) and sulfur (S)), amount of roots, etc. The range of soil data collected during a soil survey, varies with scale, specifications of a country or a region, and projected applications of the data (i.e. type of soil surveys, routine versus specifically designed surveys). As a result, the availability of soil properties differs in different soil databases. However, soil hydraulic and thermal parameters as well as biogeochemical parameters are usually not observed in soil surveys, which need to be estimated by pedotransfer functions (PTFs) (Looy et al., 2017). This review focus on the soil data (usually time-invariant) from soil surveys, while variables such as soil temperature and soil moisture are beyond this paper's scope.

Soil properties are functioned in three aspects in ESMs:

1) Model inputs to estimate parameters. The soil thermal (soil heat capacity and the thermal conductivity) and hydraulic characteristics (empirical parameters of soil water retention curve and hydraulic conductivity) are usually obtained by fitting equations (PTFs) to easily measured and widely available soil properties, such as sand, silt and clay fractions, organic matter content, rock fragments and bulk density (Clapp and Hornberger, 1978; Farouki, 1981; Vereecken et al., 2010; Dai et al., 2013). Soil albedos are significantly correlated with Munsell soil color value (Post et al., 2000). For some ESMs, the derived parameters by PTFs are used as direct input

instead of calculating them in the models.

2) Initial variables. The nutrient (C, N, P, K, S, etc.) amounts and the nutrients associated parameters (pH, cation-exchange capacity, etc.) in soils can be used to initialize the simulations. Generally, their initial values are assumed to be at steady state by running model over thousands of model years (i.e., spin-up) until no trend of change in pool sizes (McGuire et al., 1997; Thornton and Rosenbloom, 2005; Doney et al., 2006; Luo et al., 2016). To initialize nutrient amounts using soil data derived from observations as background field could largely reduce the times of model spin-up, and also could avoid the possibility of the non-linear singularity evolution of the modeling which means that that models may have multiple equilibria, and then provide better estimate of the true terrestrial nutrient state. The setting of initial nutrient stocks is a major factor leading to model-to-model variation in the simulation (Todd-Brown et al., 2014).

3) Benchmark data. Soil data, as measurements, could serve as a reference for modeling calibration, validation and comparison. Soil carbon stock is one of the most frequently used soil properties as benchmark data (Todd-Brown et al., 2013). Other nutrient stocks such as nitrogen stock can also be used as benchmark data if an ESM simulated them.

Soil properties are of great spatial heterogeneity both horizontally and vertically. As a result, ESMs usually incorporate soil property maps (i.e., horizontal spatial distribution) for multiply layers rather than a global constant or a single layer. ESMs, especially LSMs, are evolving towards hyper-resolutions of 1km or finer with more detailed parameterization schemes to accommodate the land surface heterogeneity (Singh et al., 2015; Ji et al., 2017). So spatially explicit soil data at high resolutions are necessary to improve land surface representation and simulation. Because soil properties are observed at individual locations, soil mapping or spatial prediction model is needed to derive the 3D representation of soil distribution. The traditional way (i.e., the linkage method, also called taxotransfer rule-based method) is to link soil profiles and soil mapping units on soil type maps, sometimes with ancillary maps such as topography and land use (Batjes, 2003; FAO/IIASA/ISRIC/ISS-CAS/JRC, 2012). In the past decades, various digital soil mapping technologies were proposed by finding the relationships between soil and environmental covariates (usually remote sensing data) such as climate, topography, land use, geology and so on (McBratney et al., 2003).

There are many challenges related to application of soil datasets in ESMs. First, soil datasets are usually not appropriated scaled or formatted for the use of ESMs and some upscaling issues, which is the most frequently encountered, need to be addressed. The soil datasets produced by the linkage methods are polygon-based and need to be converted to fit the grid-based ESMs. This conversion can be done by either subgrid method or spatial aggregation. The up-to-date soil data are provided at a resolution of 1km or finer, while the LSMs are mostly ran at a coarser resolution. So upscaling of soil data is necessary before it can be used by ESMs. Proper upscaling methods need to be chosen carefully to minimize uncertainty in the modeling results introduced by them (Hoffmann and Christian Biernath, 2016; Kuhnert et al., 2017).

Second, all the current global soil datasets represent the average state of last decades, and producing soil property maps in time series is still challenging. Soil landscape and pedogenic models are developed to simulate soil forming processes and soil property changes, which can be incorporated into ESMs. The prediction of changing soil properties can be also done by digital soil mapping taken the changing climate and land use as covariates. Third, the uncertainty of soil properties can be estimated, and adaptive surrogate modeling based on statistical regression and machine learning may be used to assess effects of the uncertainty of soil properties on ESMs (Gong et al., 2015; Li et al. 2018). Last but not the least, the layer schemes of soil data sets need to be converted for model use and missing values for deeper soil layers needs to be filled.

This paper is organized in the following sections. In section 2, we first introduce soil datasets at global and national scales produced by the linkage method and digital soil mapping technology and then the soil datasets that have already been incorporated in ESMs. Section 3 presents PTFs that are used in ESMs to estimate soil hydraulic and thermal parameters. Section 4 describes how to deal with soil data derived by the linkage methods. Section 5 introduces the upscaling of high-resolution soil data to the coarse resolution of ESMs. Section 6 gives the summary and an outlook of further improvements.

2 General methodology of deriving soil datasets for ESMs

2.1 Global and national soil datasets

Two kinds of soil data are generated from soil surveys: a map (usually in the form of polygon maps) representing main soil types in a landscape unit and soil profiles with observations of soil properties which are considered representative for the main component soils of the respective mapping units. ESMs usually require the spatial distribution of soil properties (i.e., soil property maps) rather than information about soil types. Two kinds of methods, i.e. the linkage method and the digital soil mapping method, are used to derive soil property maps.

Soil maps (the term soil map refers to soil type map in this paper) show the geographical distribution of soil types, which are compiled under a certain soil classification system. There are many soil mapping units (SMU) in a soil map and a SMU is composed of more than one component (i.e. soil type) in most cases. At the global level, there is only one generally accepted global soil map, i.e., the FAO-UNESCO Soil Map of the World (SMW) (FAO, 1971-1981). It was made based on soil surveys conducted between the 1930s and the 1970s, and technology available in 1960s. Several versions exist in the digital format (FAO, 1995, 2003b; Zöbler, 1986) and these products are known to be outdated. The information on the initial SMW and DSMW has since been updated for large sections of the world in the HWSD product (FAO/IIASA/ISRIC/ISS-CAS/JRC, 2012), which has recently been revised in WISE30sec (Batjes, 2016).

At the regional and national level, there are many soil maps based on either national or international soil classifications. Here are some examples of major soil maps available in digital formats: the Soil and Terrain Database (SOTER) databases

(Van Engelen and Dijkshoorn, 2012) for different regions, the European Soil Database (ESB, 2004), the 1: 1 million Soil Map of China (National Soil Survey Office, 1995), the U.S. General Soil Map (GSM), the 1:1 million Soil Map of Canada (Soil Landscapes of Canada Working Group, 2010) and the Australian Soil Resource Information System (ASRIS) (Johnston et al., 2003).

Soil profiles are composed of multiple layers called soil horizons. For each horizon, soil properties are observed (e.g. site data) or measured (e.g. pH, sand, silt, clay content). At the global level, several soil profile databases exist. Here we only discuss the two most comprehensive ones. The World Inventory of Soil Emission Potentials (WISE) database was developed as a homogenized set of soil profiles (Batjes, 2008). The newest version (WISE 3.1) contains 10,253 soil profiles and 26 physical and chemical properties. The soil profiles database of World Soil Information Service (WoSIS) contains the most abundant profiles (about 118,400) from national and global databases including most of the databases mentioned below (Batjes et al., 2017), though only a selection of important soil properties (12) are included (Ribeiro et al., 2018). Data served through WoSIS have been standardized, with special attention for the description and comparability of soil analytical methods worldwide. However, many countries, although having a large collection of soil profile data, are not yet sharing such data (Arrouays et al, 2017).

At the regional and national level, there are many soil profile databases, usually with soil classifications corresponding to the local soil maps. Here are some examples: the USA National Cooperative Soil Survey Soil Characterization database (http://ncsslabdatamart.sc.egov.usda.gov/), profiles from the USA National Soil Information System (http://soils.usda.gov/technical/nasis/), Africa Soil Profiles database (Leenaars, 2012), the Australian Soil Resource Information System (Karssies, 2011), the Chinese National Soil Profile database (Shangguan et al., 2013), soil profile archive from the Canadian Soil Information System (MacDonald and Valentine, 1992), soil profiles from SOTER (Van Engelen and Dijkshoorn, 2012), the soil profile analytical database for Europe (Hannam et al., 2009), the Mexico soil profile database (Instituto Nacional de Estadística y Geografía, 2016), and the Brazilian national soil profile database (Cooper et al., 2005).

The linkage method (called the taxotransfer rule-based method) is to link soil maps (with soil mapping units or soil polygons) and soil profiles (with soil properties) according to taxonomy-based pedotransfer (taxotransfer in short, note that pedotransfer here does mean pedotransfer functions which is a different thing) rules (Batjes, 2003). The criteria used in the linkage could be one or many factors as following: soil class, soil texture class, depth zone, topographic class, distance between soil polygons and soil profiles and so on (Shangguan et al., 2012). Each soil type is represented by one or a group of soil profiles that meet the criteria, and usually the median or mean value of a soil property is assigned to the soil type. Because the linkage method assigned only one value or a statistical distribution to a soil type in soil polygons (usually a polygon contains multiple soil types with their fractions), the intra-polygonal spatial variation is not taken into account. At the global level, many databases were derived by the linkage method: the FAO Soil Map of the World with derived soil properties (FAO, 2003a), the Data and Information System of International Geosphere-Biosphere Programme (IGBP-DIS) database (Global Soil DataTask, 2000), the Soil and Terrain Database (Van Engelen and Dijkshoorn, 2012) for multiply regions and countries, the ISRIC-WISE derived soil property maps (Batjes, 2006), the Harmonized World Soil Database (HWSD) (FAO/IIASA/ISRIC/ISS-CAS/JRC, 2012), the Global Soil Dataset for Earth System Model (GSDE) (Shangguan et al., 2014) and WISE30sec (Batjes, 2016). Three most recent ones are HWSD, GSDE and WISE30sec. HWSD was built via combining the existing regional and national updates of soil information. GSDE as an improvement of HWSD incorporated more soil maps and more soil profiles related to the soil maps, with more soil properties. GSDE accomplished the linkage based on the local soil classification, which required no correlation between classification systems and avoided the error brought by taxonomy reference. In addition, GSDE provides estimation of eight layers to the depth of 2.3 m, while HWSD provides estimation of two layers to the depth of 1 m. WISE30sec is another improvement of HWSD incorporated more soil profiles with seven layers up to 200 cm depth and with uncertainty estimated by mean ± standard deviation. WISE30sec used the soil map from HWSD with minor corrections and climate zone maps as categorical covariate. Many national and regional agencies around the world have organized their soil surveys by linking soil maps and soil profiles, including the USA State Soil Geographic Database (STATSGO2) (Soil Survey Staff, 2017), Soil Landscapes of Canada (Soil Landscapes of Canada Working Group, 2010), the ASRIS (Johnston et al., 2003), the Soil-Geographic Database of Russia (Shoba et al., 2008) the European Soil Database (ESB, 2004), the China dataset of soil properties (Shangguan et al., 2013) and so on.

Digital soil mapping (McBratney et al., 2003) is the creation and the population of a geographically referenced soil database, generated at a given resolution by using field and laboratory observation methods coupled with environmental data through quantitative relationships (http://digitalsoilmapping.org/). Usually, the soil datasets derived by digital soil mapping provide grid-based spatial continuous estimation while the soil datasets derived by the linkage method provide estimations with abrupt changes at the boundary of soil polygons. The GlobalSoilMap is a global consortium that aims to create global digital maps for key soil properties (Sanchez et al., 2009). This global effort takes a bottom-up framework and will produce the best available map of soil at a resolution of 3 arc sec (about 100 m) along with the 90% confidence of predictions. Soil properties will be provided for six soil layers (i.e. 0–5, 5–15, 15–30, 30– 60, 60–100, and 100–200 cm). Many countries have produced soil maps following the GlobalSoilMap specifications (Odgers et al., 2012; Viscarra Rossel et al., 2015; Mulder et al., 2016; Ballabio et al., 2016; Ramcharan et al., 2018; Arrouays, 2018). The Soilgrids system (https://www.soilgrids.org) is another global soil mapping project (Hengl et al., 2014; Hengl et al., 2015; Hengl et al., 2017). The newest version (Hengl et al., 2017) at a resolution of 250 m was produced by fitting an ensemble of machine learning methods based on about 150,000 soil profiles and 158 soil covariates, which is currently the most detailed estimation of global soil distribution. A third global soil mapping project is the Global SOC Map of the Global Soil Partnership, which focuses on country-specific soil organic carbon estimates (Guevara et al., 2018).

Because soil property maps are derived products based on soil measurements of soil profiles (point observations) and spatial continuous covariates (including soil maps), it is necessary to discuss the uncertainty sources, spatial uncertainty estimation and accuracy assessment of these derived data (the last two are different aspects of uncertainty estimation). More attention should be paid to this issue in ESM applications instead of taking soil property maps as observations without error. There are various uncertainty sources in deriving soil property maps, including uncertainty from soil maps, soil measurements, soil-related covariates and the linkage method itself (Shangguan et al., 2012; Batjes, 2016; Stoorvogel et al., 2017). The following may not be the complete list of uncertainty but the major ones. The uncertainty of soil maps is a major source of global dataset derived by the linkage methods. For these dataset, large sections of the world are drawn on the coarse FAO SMW map and the purity of soil maps (referring to the following website for the definition: https://esdac.jrc.ec.europa.eu/ESDB_Archive/ESDBv2/esdb/sgdbe/metadata/purity_maps/purity.htm) is likely to be around 50 to 65% (Landon, 1991). Another important source of uncertainty is the limited comparability of different analytical methods of a given soil property in using soil profiles coming from various sources. A weak correlation or even a negative correlation was found between different analytical methods, though strong positive correlation revealed in most cases (McLellan et al. 2013). Both datasets by the linkage method and those by digital soil mapping suffer this uncertainty. Though there are no straightforward mechanisms to harmonize the data, efforts are undertaken to address this issue and provide quality assess (Batjes, 2017; Pillar 5 Working Group, 2017). Another source of uncertainty comes from the geographic and taxonomic distribution of soil profiles, especially for the under-represented areas and soils (Batjes, 2016). The fourth source of uncertainty is from the linkage method itself. It does not represent the intra-polygon spatial variation and usually do not consider soilrelated covariates explicitly like digital soil mapping, though there are cases where climate and topography are considered and Stoorvogel et al. (2017) proposed a methodology to incorporate landscape properties in the linkage method. Finally, uncertainty from the covariates is minor because spatial prediction models such as machining learning in digital soil mapping can reduce its influences (Hengl et al., 2014), though a more comprehensive list of covariates with higher resolution and accuracy will improve the predicted soil property maps. Spatial uncertainty is estimated by different methods for the linkage method and digital soil mapping methods. For the linkage method, statistics such as standard derivation and percentiles can be used as spatial uncertainty estimation, which are calculated for the population of soil profiles linked to a soil type or a land unit (Batjes, 2016). This estimation has some limitations because soil profiles are not taken probabilistically but based on their availability, especially for the global soil datasets. Uncertainty will be underestimated when the sample size is not big enough to represent a soil type. For digital soil mapping, spatial uncertainty could be estimated by methods such as geostatistical methods and quantile regression forest (Vaysse and Lagacherie, 2017), which make sense of statistic. The accuracy of soil dataset derived by digital soil mapping are estimated by cross-validation. But it is not trivial for those derived by the linkage method due to the global scale, the support of the data and independent data (Stoorvogel et al., 2017) and most of these maps are validated by statistics such as mean error and coefficient of determination. Instead, some datasets, including WISE and GSDE, use some indictors such as linkage level of soil class and sample size to offer quality control information (Shangguan et al. 2014; Batjes, 2016). A simple way to compare the accuracy of datasets by both methods may be to use a global soil profile database as a validation dataset, though some of these profiles were used in deriving these datasets and questions will be raised. We evaluated several global soil property maps in section 3.

2.2 Soil dataset incorporated in ESMs

Table 1 shows ESMs (specifically, their land surface models) and their input soil datasets. The ESMs in Table 1 cover the list of CMIP5 (Coupled Model Intercomparison Project) except those without information about the input soil datasets. Land surface models (LSMs) are key tools to predict the dynamic of land surface under climate change and land use. Five datasets are widely used, i.e., the datasets by Wilson and Henderson-Sellers (1985), Zöbler (1986), Webb et al. (1993), Reynolds et al. (2000), Global Soil Data Task (2000), and Miller and White (1998). Except GSDE, HWSDand STATSGO (Miller and White, 1998) for USA in Table 1, these datasets were derived from the Soil Map of the World (note that large sections of GSDE and HWSD still used this map as a base map because there are no available regional or national maps) (FAO, 1971-1981) and limited soil profile data (no more than 5,800 profiles), which gained popularity because its simplicity and ease of use. But these are outdated and should no longer be used because much better soil information as introduced in Section 2.1 can be incorporated (Sanchez et al., 2009; FAO/IIASA/ISRIC/ISS-CAS/JRC, 2012).

In recent years, efforts were taken to improve the soil data condition in ESMs. The Land-Atmosphere Interaction Research Group at Beijing Normal University (BNU, now at Sun Yat-sen University) has put much efforts on this topic. Shangguan et al. (2012, 2013) developed a China dataset of soil properties for land surface modeling based on 8,979 soil profiles and the Soil Map of China using the linkage method. Dai et al. (2013) derived soil hydraulic parameters using pedotransfer functions based on the soil properties by Shangguan et al. (2013). Shangguan et al. (2014) further developed a comprehensive global dataset for ESMs. The above soil datasets were widely used in the ESMs. Soil properties from these soil datasets, including soil texture fraction, organic carbon, bulk density and derived soil hydraulic parameters, were implemented in the Common Land Model Version 2014 (CoLM2014, http://land.sysu.edu.cn/). Li et al. (2017) shows that CoLM2014 was more stable than the previous version and had comparable performance to that of CLM4.5 which may be attributed in part to the new soil parameters as input. Wu et al.

(2014) shows that soil moisture values are closer to the observations when simulated by CLM3.5 with the China dataset than those simulated with FAO. Zheng and Yang (2016) estimated effects of soil texture datasets from FAO and BNU on regional terrestrial water cycle simulations with the Noah-MP land surface model. Tian et al. (2012) used the China soil texture data in a land surface model (GWSiB) coupled with a groundwater model. Lei et al. (2014) used the China soil texture data in CLM to estimate the impacts of climate change and vegetation dynamics on runoff in the mountainous region of the Haihe River basin. Zhou et al. (2015) estimated age-dependent forest carbon sink with a terrestrial ecosystem model utilizing the soil carbon data of China. Dy and Fung (2016) updated the soil data for the Weather Research and Forecasting model (WRF).

Researchers have also put efforts to update ESMs with other soil data. Lawrence and Chase (2007) used MODIS data to derive soil reflectance, which was used as a soil colour parameter in Community Land Model 3.0 (CLM). De Lannoy et al. (2014) updated the Catchment land surface model of the NASA with soil texture and organic matter data from HWSD and STATSGO2. Livneh et al. (2015) evaluated the influence of soil textural properties on hydrologic fluxes by comparing the FAO data and STATSGO2. Folberth et al. (2016) evaluated the impact of soil input data on yield estimates in a global gridded crop model. Slevin et al. (2017) utilized the HWSD to simulate global gross primary productivity in the JULES land surface model. Trinh et al. (2018) proposed an approach that can assimilate coarse global soil data by finer land use and coverage dataset which improved the performance of hydrologic modeling at watershed scale. Kearney and Maino (2018) incorporated the new generation of soil data produced by digital soil mapping method into a climate model and found that, compared to the old soil information, this improved the simulation of soil moisture at fine spatial and temporal resolution over Australia. A global gridded hydrologic soil groups (HYSOGs250m) was developed based on soil texture and depth to bedrock of Soilgrids (Hengl et al., 2017) and groundwater table depth (Fan et al., 2013) for curve-number based runoff modeling of U.S. Department of Agriculture (Ross et al., 2018).

Except soil properties, the estimation of underground boundaries including the groundwater table depth, the depth to bedrock (DTB) and depth to regolith and its implementation in ESMs is also a new focus. Fan et al. (2013) compiled global observations of water table depth and inferred the global patterns using a groundwater model. Pelletier et al. (2016) developed a global DTB dataset by using process-based models for upland and an empirical model for lowland. This dataset was implemented in the CLM4.5 and found that there were significant influences on water and energy simulations compared to the default constant depth (Brunke et al., 2015). Shangguan et al. (2018) developed a global DTB by digital soil mapping based on about 1.7 million observations from soil profiles and water wells, which has a much higher accuracy than the dataset by Pelletier et al. (2016). Vrettas and Fung (2016) shows that the weathered bedrock stores a significant fraction (more than 30%) of the total water despite its low porosity. Jordan et al. (2018) estimated global permeability of the unconsolidated and consolidated earth for groundwater modelling. However, due to the lack of data, an accurate global estimation of depth to regolith is not feasible. Caution should be paid to use of the products of so-called soil depth in ESMs. Soil depth maps are usually estimated based on observations from soil survey, and soil depth (or depth to the R horizon) is assumed to be equal to DTB. However, these observations are usually less than 2 meters and usually do not meet the depth to bedrock (Shangguan et al., 2017). Thus, soil depth maps based on soil profiles only are significantly underestimated (one order of magnitude lower) compared to the actual depth to bedrock and should not be taken as the lower boundary of ESMs.

2.3 Estimating secondary parameters using pedotransfer functions

Earth system modellers have employed different pedotransfer functions (PTFs) to estimate soil hydraulic parameters (SHP), soil thermal parameters (STP), and biogeochemical parameters (Looy et al., 2017; Dai et al., 2013) or used these parameters as model inputs. Almost all ESMs incorporated SHPs and STPs estimated by PTFs but not biogeochemical parameters. PTFs are the empirical functions that account for the relationships between these secondary parameters (i.e., derived soil properties) and more easily obtainable soil property data. Direct measurement of these parameters is difficult, expensive and in most cases impractical to take sufficient samples to reflect the spatial variation. Thus, most soil databases do not contain these secondary parameters. PTFs provide the alternative to estimate them. In ESMs, SHPs and STPs are usually derived using simple PTFs taking only soil texture data as the input. As more soil properties become available globally, including gravel, soil organic matter and bulk density, more sophisticated PTFs using additional soil properties can be utilized in ESMs.

PTFs can be expressed as either numerical equations or by machine learning methodology which is more flexible to simulate the highly nonlinear relationship in analysed data. PTFs can also be developed based on soil processes. Most researches did not indicate where the PTFs can potentially be used, and the accuracy of a PTF outside of its development dataset is essentially unknown McBratney et al. (2011). PTFs generally are not portable from one region to the other (i.e. locally or regionally validated). Therefore, they should never be considered as an ultimate source of parameters in soil modelling. Looy et al. (2017) reviewed PTFs extensively in earth system science and emphasized that PTF development has to go hand in hand with suitable extrapolation and upscaling techniques such that the PTFs correctly represent the spatial heterogeneity of soils in ESMs. Though the PTFs were evaluated, it is not clear which are the best set of PTFs for global applications. Due to these limitations, a better way to estimate the secondary parameters may be to use an ensemble of PTFs, which can give the variability of parameters. Dai et al. (2013) derived a global soil hydraulic parameter database using the ensemble method. Selection of PTFs was carried out based on the following rules, including the consistent physic definition, large enough training sample and positive evaluations in comparison with other PTFs. The PTFs selected included not only those in equations but also PTFs of machine learning. As a result, the modellers could use these parameters as inputs instead of calculating them in ESMs every time running the model.

The new generation soil information has already been utilized to derive SHPs and STPs in some researches. Montzka et al. (2017) produced a global map of SHPs at a resolution of 0.25° based on the SoilGrids 1km dataset. Tóth et al. (2017) calculated SHPs for Europe with the EU-HYDI PTFs (Tóth et al., 2015) based on SoilGrids 250 m. Wu et al. (2018) used an integrated approach that ensembles PTFs to map field capacity of China based on multi-source soil datasets.

The performance of PTF in ESMs is evaluated in many researches, though PTFs has not been fully exploited and integrated into ESMs (Looy et al., 2017). Here are some examples. Chen et al. (2012) incorporated soil organic matter to estimate soil porosity and thermal parameters for the use of land surface models. Zhao et al. (2018a) evaluated PTFs performance to estimate SHPs and STPs for land surface modelling over the Tibetan Plateau. Zheng et al. (2018) developed PTFs to estimate the soil optical parameters to derive soil albedo for the Tibetan Plateau, and the PTFs incorporated into an eco-hydrological model which improved the model simulation of surface energy budget. Looy et al. (2017) envisaged two possible approaches to improve parameterization of Earth system models by PTFs. One is to replace constant coefficients in the current ESMs with spatially distributed values by PTFs. The other is to develop spatially exploitable PTFs to parameterize specific processes using knowledge of environmental controls and variation of soil properties.

3 Comparison of available global soil datasets

For the convenience of ESMs' application, we compared several available soil datasets and evaluated them with soil profiles from WoSIS for some key variables (Sand, clay content, organic carbon, coarse fragment and bulk density) used in ESMs. In addition to the most recent developed soil datasets, we also included one old data set (i.e. IGBP) used in ESMs for the evaluation. It is not necessary to compare all the old data sets because they are based on similar, limited and outdated source data as described in section 2.2. They have coarser resolution (Table 1) than the newly developed soil datasets (Table 2).

We present basic descriptions about the new soil datasets in Table 2 and 3. As described in section 2.1, four available global soil datasets, i.e. HWSD, GSDE, WISE30sec and Soilgrids, have been developed in the last several years (Table 2). These soil datasets are selected to be shown here because they have a global coverage with key variables used by ESMs and developed with relatively good data sources in recent years, and are freely available. Old versions of these datasets are not shown here. Table 3 shows the available soil properties of these soil datasets. Except WISE30sec, all these databases do not contain spatial uncertainty estimation. The explained variance of soil properties in Soilgrids is between 56% and 83%, while the other datasets do not offer quantitative accuracy assessment. GSDE has the largest number of soil properties, while Soilgrids currently contains ten primary soil properties defined by the GlobalSoilMap consortium.

The accuracy of the newly developed soil datasets (Soilgrids, GSDE and HWSD) and an old dataset (IGBP) are evaluated for five key variables using 94,441 soil profiles from WoSIS (Table 4). We used four statistics in the evaluation, including mean error

(ME), root mean squared error (RMSE), coefficient of variation (CV) and coefficient of determination (R^2). All soil datasets are evaluated for topsoil (0-30cm) and subsoil (30-100cm). The layer schemes of soil datasets are different (Table 1) and they were converted to the two layers. Soil datasets are in high resolution and were converted to the resolution of 10 km by averaging. All datasets have relatively small ME. In general. Soilgrids has much better accuracy than the other three due to RMSE, CV and R^2, and GSDE ranks the second, followed by IGBP and HWSD. However, IGBP is slightly better than GSDE for bulk density and organic carbon of topsoil. Note that the IGBP does contain coarse fragment, which is needed in calculating soil carbon stocks. We did not evaluate the WISE30sec here to save some time in data processing, because previous evaluation using WoSIS showed that WISE30sec had slightly better accuracy than HWSD (https://github.com/thengl/SoilGrids250m/tree/master/grids/HWSD). This evaluation has some limitations. First, because the datasets developed by the linkage method give the mean value of a SMU resulted in abrupt change between the boundaries of soil polygons while the datasets developed by digital soil mapping simulated the soil as a continuum with a spatial continuous change of soil properties, they may not be so comparable. Second, the original resolution of soil datasets are different, which means that maps with higher resolution provides more spatial details and we should judge the map quality due to not only the accuracy assessment but also the resolution. As a result, datasets with higher resolution (i.e. HWSD and GSDE) are preferred than that with lower resolution (i.e., IGBP) as they have similar accuracy, especially when the LSMs are run at a high resolution such as 1km. Third, the vertical variation are better represented by Soilgrids, GSDE and WISE30sec with more than 2 layers and to a depth over 2m (Table 2). This will provide more useful information for ESMs, especially when they model deeper soils with multiply layers.

The new generation soil dataset produced by digital soil mapping method gave a quite different distribution of soil properties from those produced by the linkage method. Figure 1 shows soil sand and clay fraction at the surface 0-30 cm layer from Soilgrids, IGBP and GSDE. Figure 2 shows soil organic carbon and bulk density at the surface 0-30 cm layer from Soilgrids, IGBP and GSDE. Significant differences are visible in these datasets. This will lead to different modelling results in ESMs. Tifafi et al. (2018) found that the global soil organic carbon stocks down to a depth of 1m is 3,400 Pg estimated by Soilgrids while it is 2500 Pg by HWSD, and the estimates by Soilgrids are closer to the observations, though they all underestimated the soil carbon stocks. Figure 1 of Tifafi et al. (2018) showed the global distribution of soil carbon stocks by Soilgrids and HWSD.

In general, Soilgrids is preferred for ESMs' application as it has the highest accuracy and resolution at the time. When soil properties are not available in Soilgrids, WISE30sec and GSDE offers the alternative options. However, model sensitivity simulations need to be done to investigate the effects of different soil datasets on ESMs in future studies.

4 Soil data usage in ESMs and existing challenges

4.1 Model use of soil data derived by the linkage method

Soil data by the linkage method are derived for each soil mapping unit or land unit and thus is polygon-based, while ESMs are usually grid-based. However, soil data derived by digital soil mapping are grid-based. So, the compatibility between soil data derived by the linkage method and ESMs needs to be addressed. In the soil map, a soil mapping unit (SMU) is composed of more than one component soil unit in most cases, and thus a one-to-many relationship exists between the SMU and the profile attributes of the respective soil units. This condition makes representing attributes characterizing a SMU a non-trivial task. To keep the whole variation of soil in a SMU, the best way is using the subgrid method in ESMs (Oleson et al., 2010), i.e. aggregate values of soil properties and provide the area percentage of each value. This will bring the problem of how to map the soil subgrids with land cover (or plant function type) subgrids. A possible solution is to: classify soil according to soil properties and get a number of defined soil classes (SC, n classes) like land cover types (LCT, m classes); overlay the defined soil classes with land cover types and get n by m combinations assuming soil classes and land cover types are independent. However, this will increase the computing time and the complexity of ESMs' structure, which needs to implement the soil processes over each subgrid soil column within a grid instead of the entire model grid.

Usually, the compatibility issue is addressed by converting the SMU-based soil data to grid data using spatial aggregation. The ESMs uses grid data as input and each grid cell has one unique value of a soil property. Three spatial aggregation methods were proposed to aggregate compositional attributes in a SMU to a representative value (Batjes, 2006; Shangguan et al., 2014). The area-weighting method (method A) takes area-weighting of soil attributes. The dominant type method (method D) takes the soil attribute of the dominant type. The dominant binned method (method B) classifies the soil attribute into several preselected classes and takes the dominant class. All three methods can be applied to quantitative data, while the method D and the method B can be applied to categorical data. The advantages and disadvantages of these methods were discussed (Batjes, 2006; Shangguan et al., 2014). The choice should be made according to the specific applications (Hoffmann and Christian Biernath, 2016). The method B provides binned classes, which are not convenient for modelling, though method B is considered more appropriate to represent a grid cell. The method A keeps mass conservation, which can meet most demands of model applications. However, the method A may be misleading in cases when extreme values appeared in a SMU. For the linkage method, the uncertainty is usually estimated by giving the 5 and 95 percentile soil properties (or other statistics) of the soil profiles that linked to a SMU. Because the frequency distribution of soil properties within a SMU is usually not a normal distribution or any other typical statistic distribution, the application of statistics such as standard deviation in model use is not proper. This means that the uncertainty of soil dataset derived by the linkage method can not be incorporated into ESMs in a straight forward way, and technology such as bootstrap may be more suitable than methods making assumptions on the distribution.

The basic soil properties are often used to derive secondary parameters including SHPs and STPs by PTFs and soil carbon stock or other nutrient stocks by certain equations (Shangguan et al., 2014). This procedure could be done either before or after the aggregation (here referred to ‘‘aggregating after” and ‘‘aggregating first’’). Because the relationship between the soil basic properties and the derived soil parameters is usually nonlinear, the ‘‘aggregating first’’ method should be taken. This was also proved by case studies (Romanowicz et al., 2005; Shangguan et al., 2014). However, some researches used the ‘‘aggregating after” method producing misleading results (Hiederer and Köchy, 2012).

The aggregation smooths the variation of soil properties between soil components within a given SMU (Odgers et al., 2012). To avoid the aggregation, the spatial disaggregation of soil type maps can be used to determine the location of the SMU components, though the location error may be high in some cases (Thompson et al., 2010; Stoorvogel et al., 2017). This method depends on high density of soil profiles to establish soil and landscape relationships. Folberth et al. (2016) shows that the correct spatial allocation of the soil type to present cropland was very important in global crop yield simulations. Currently, aggregation is still the pragmatic way at the global scale due to lack of data.

4.2 Upscaling detailed soil data for model use

The updated soil datasets derived by both the linkage method and digital soil mapping are usually at a resolution from 1 km to 100 m, and upscaling or aggregation is required to derive lower resolution datasets for model use. The aggregation methods mentioned above can be used. Moreover, there are plenty of upscaling methods such as the window median, variability-weighted methods (Wang et al., 2004), variogram method (Oz et al., 2002), fractal theory (Quattrochi et al., 2001) and Miller–Miller scaling approach (Montzka et al., 2017). However, few studies have been devoted to test out which upscaling methods are suitable for soil data. A preliminary effort was done by (Shangguan, 2014). Five upscaling methods compared were the window average, widow median, widow modal, arithmetic average variability-weighted method and bilinear interpolation method. Differences between aggregation methods varied from 10% to 100% for different parameters. The upscaling methods affected the data derived by the linkage method more than the data by digital soil mapping. The window average, window median and arithmetic average variability-weighted method performed similar in upscaling. The root mean square error increased rapidly when the window size was less than 40 pixels. Similar to the aggregation of SMUs, the “aggregating first” method is recommended when secondary soil parameters are derived. Again, alternative to avoid the aggregation into one single value for a grid cell is to use the subgrid methods in ESMs.

The upscaling effect of soil data on model simulation has been investigated in previous studies with controversial conclusions. For example, Melton et al. (2017) used two linked algorithms to provide tiles of representative soil textures for subgrids in a terrestrial ecosystem model and found that the model is relatively insensitive to subgrid soil textures compared to a simple grid-mean soil texture at a global scale. However, the treatment without soil subgrid structure in JULES resulted in soil-moisture dependent anomalies in simulated carbon flux (Park et al., 2018). Further researches are necessary to investigate the upscaling effect on models.

4.3 The changing soil properties

There is not any global soil property map in time-series because we do not have enough available data. In all the global soil property maps, all the available soil observations in the last decades are used in the development of soil property maps without considering the changing environment. So these datasets should be considered as an average state. The critical issue for mapping global soil properties in time-series is to establish a soil profile database with time stamps and then divide them into two or more groups of different periods such as 1950s-1970s. This is still quite challenging at the global scale because the spatial coverage of soil profiles is quite uneven for different periods and the sample size may not be big enough to derive maps with satisfied accuracy.

Soil properties are changing but we are now taking it as static in ESMs. As some ESMs already simulate the soil carbon, this may be considered in PTFs used to estimate soil hydraulic and thermal parameters. Other soil properties affecting soil hydraulic and thermal parameters include soil texture, bulk density, soil structure and so on, but the change is relatively slow. The effect of environmental change on soil properties is the topic of quantitative modeling of soil forming processes, i.e. soil landscape and pedogenic models (Gessler et al., 1995; Minasny et al., 2008). If we need to simulate the change of soil properties, a coupling of ESMs and soil landscape and pedogenic models will be needed. Otherwise, we need to predict the soil properties in the future using soil landscape and pedogenic models which are small scale models and has high uncertainty. The prediction of changing soil properties may also be done by digital soil mapping taken the changing (especially for the future) climate and land use as covariates, which may be the more feasible than dynamic models.

4.4 Incorporating the uncertainty of soil data in ESMs

Incorporating the uncertainty of soil data in ESMs is a rising challenge. Except WISE30sec, all the current global soil data sets do not have a corresponding uncertainty map for a soil property. But the spatial uncertainty can be estimated by the methods mentioned in section 2.1 and soil data sets with uncertainty map will be made available sooner or later. It is too expensive to run multiply ESM simulations combining upper and lower bounds in all possible combinations to quantify the effect of soil data uncertainty on ESMs. Instead, adaptive surrogate modeling based on statistical regression and machine learning can be used, which costs much lower computing time and proves to be effective and efficient (Gong et al., 2015; Li et al. 2018). Surrogate models are used to emulate the responses of ESMs to the variation of soil properties at each location.

4.5 Layer schemes and lack of deep layer soil data

The layer scheme of a soil data set needs to be coveted to that of ESMs for model use. A simple way for this conversion is the depth weighting method. When a more accurate conversion is needed, the equal-area quadratic smoothing spline functions can be used, which is proved to be advantageous in predicting the depth function of soil properties (Bishop et al., 1999). Mass conservation for a soil property of a layer is guaranteed by this method under the assumption of continuous vertical variation of soil properties. This method may produce some negative values which should be set to zero.

The depth of soil observations in soil survey are usually less than 2 m and thus resulted in missing values for the deep layers of ESMs. For the lack of deep soil data, there is not any good solution other than extrapolate the values based on the observations of shallower layers, which will lead to higher uncertainty of soil properties for deep layers. The extrapolation can be done by the above-mentioned spline method or simply by assigning soil properties of the last layer to the rest of deeper soil layers. Depth to bedrock map (Shangguan et al., 2018) can be utilized in defining the low boundary of soil layers, and a default set of thermal and hydraulic characteristic can be assigned for bedrocks.

5 Summary and outlook

This paper reviews the status of soil datasets and their usage in ESMs. Soil physical and chemical properties served as model parameters, initial variables or benchmark datasets in ESMs. Soil profiles, soil maps and soil datasets derived by the linkage method and digital soil mapping are reviewed at national, regional and global levels. The soil datasets derived by digital soil mapping are considered to provide more realistic estimation of soils than those derived by the linkage method, because digital soil mapping provide spatial continuous estimations of soil properties using spatial prediction models with various soil-related covariates. Due to the evaluation of soil datasets by WoSIS, Soilgrids have the most accurate estimation of soil properties. However, other soil datasets including GSDE and WISE30sec can be considered as they provide more soil properties.

The popular soil datasets used in ESMs are outdated and there are soil datasets available for the updates. In the recent several years, efforts were taken to update the soil data in ESMs. The effects of updated soil properties which are used to estimate soil hydraulic and thermal parameters were evaluated. Other major updates include soil reflectance, ground water tables and depth to bedrock.

Pedotransfer functions (PTFs) are employed to estimate secondary soil parameters, including soil hydraulic and thermal parameters, and biogeochemical parameters. PTFs can take more soil properties (i.e., soil organic carbon, bulk density etc.) as input in addition to soil texture data. An ensemble of PTFs may be more suitable to provide secondary soil parameters as direct input to ESMs, because ensemble method has a number of benefits and potential over a single PTF (Looy et al., 2017).

Soil data derived by the linkage methods and high-resolution data can be aggregated by different methods to fit the use in ESMs. The aggregation should be done after the secondary parameters are estimated. However, the aggregation will omit the variation of soil properties. To avoid the aggregation, the subgrid method in ESMs is an alternative which increases the model complexity. The effect of different upscaling methods on the performance of ESMs needs to be investigated further.

Because digital soil mapping has many advantages compared to the traditional linkage method, especially in representing spatial heterogeneity and quantifying uncertainty in the predictions, the new generation soil datasets derived by digital soil mapping need to be tested in ESMs, and some regional studies have shown that these datasets provided better modelling results than products by the linkage method (Kearney and Maino, 2018; Trinh et al., 2018). Moreover, many studies from digital soil mapping have identified that soil maps are not very important to predict soil properties and are usually not used as a covariate in most studies (eg. Hengl et al., 2014; Viscarra Rossel et al., 2015; Arrouays et al., 2018). However, the linkage method usually takes soil map as the major covariate, which essentially affect the accuracy of the derived soil property maps, especially for areas without detailed soil maps. As a data-driven method, digital soil mapping requires soil profiles observations and environmental covariates (in which the importance of soil maps is low), and including more of these data in mapping will improve the global predictions (Hengl et al., 2017). More quality assessed data, analysed according to comparable analytical methods, are needed to support such efforts. The harmonization of soil data is undertaking by the work of GSP Pillar 5 (Pillar 5 Working Group, 2017) and WoSIS (Batjes et al., 2017). Data derived from proximal sensing, although with higher uncertainty than traditional soil measurements, can be used in soil mapping (England and Viscarra Rossel, 2018). To avoid spatial extrapolation, soil profiles should have a good geographical coverage. The temporal variation of global soil is quite challenging due to lack of data. Soil image fusion is also needed to merge the local and global soil maps, which consider them as components of soil variation for ensemble predictions (Hengl et al., 2017). A system for automated soil image fusion might take years before an operational system for global soil data fusion is fully functional. Mapping the soil depth and depth to bedrock separately at the global level is also still challenging due to lack of data and the understanding of relevant processes. Uncertainty estimation, especially spatial uncertainty estimation should be included in the soil datasets developed in the future. However, incorporating the spatial uncertainty of soil properties in ESMs is still challenging due to the cost, and an alternative may be to use adaptive surrogate modeling.

The gap between the amount of data that has been taken in surveys and the amount of data freely available is large. The soil profiles included by global soil databases such as WoSIS make up a very small fraction of the soil pits dug by human beings. For example, there are more than 100,000 soil profiles from the second national soil survey of China (Zhang et al., 2010) and no more than 9,000 were used to produce the national soil property maps freely available (Shangguan et al., 2013). In the last century, national soil survey was accomplished widely, majorly for agriculture purpose. However, most of these legacy data are not digitalized and they are usually not made available to the science community even if digitalized. How to flush out these hidden soil data requires some mechanism such as government mandatory regulations and investing money on making them available (Pillar four Working Group, 2014; Pillar 5 Working Group, 2017). Arrouays et al. (2017) reported that about 800,000 soil profiles have been rescued in the selected countries. In addition, investments on new soil samplings should be made, especially in the under-represented areas. A good example is the US, which has the most abundant soil data freely available (Batjes et al., 2017) like many other data. If the hidden data could be made available in any way, science and the whole human being will be promoted. A true big data era is waiting for us. Censored information produces censored things. Data compatibility of different analysis methods and different description protocols including soil classifications is also an important issue and data harmonization is necessary when the data are made available to public.

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Table 1. Lists of the soil dataset used by land surface models (LSM) of Earth System Models (ESM) or climate models (CM)

Dataset	Resolution	ESM or CM	LSM	Input soil data
Elguindi et al. (2014)		RegCM	BATS1e (Dickinson et al., 1993) or CLM3.5	Soil texture classes and Soil color classes prescribed for BATS vegetation/land cover type
FAO (2003 a,b)	5’	CanESM2	CTEM (Arora et al., 2009) CLASS3.4 (Verseghy, 2000)	Soil texture
FAO (2003 a,b)	5’	EC-EARTH	HTESSEL (Orth et al., 2016)	Soil texture classes
FAO (2003 a,b; outside Conterminous US) STATSGO (Miller and White, 1998)	5’ 30”	WRF CWRF	Noah (Chen and Dudhia, 2001) Noah-MP (Niu et al., 2011) CLM4 Other LSMs	Soil texture
GSDE (Shangguan et al., 2014)	30”	CAS_ESM BNU_ESM GRAPES	CoLM 2014(Dai et al., 2003)	Soil texture, gravel, soil organic carbon, bulk density
GSDE (Shangguan et al., 2014)	30”	WRF CWRF	Noah (Chen and Dudhia, 2001) Noah-MP (Niu et al., 2011) CLM4 Other LSMs	Soil texture
GSDE (Shangguan et al., 2014)	30”	BCC_CSM 1.1 BCC_CSM 1.1(m)	BCC_AVIM 1.1 (Wu et al., 2014)	Soil texture
Hagemann (2002)	0.5° (8km over Africa)	MPI-ESM ICON-ESM	JSBACH4 (Mauritsen et al. (2019)	Soil albedo

Hagemann (2002)	0.5°	MPI-ESM ICON-ESM	JSBACH4 (Mauritsen et al. (2019)	Field capacity, Plant-available soil water holding capacity and wilting point prescribed for ecosystem type
Hagemann et al. (1999)	0.5°	MPI-ESM ICON-ESM	JSBACH4 (Mauritsen et al. (2019)	Volumetric heat capacity and thermal diffusivity prescribed for 5 soil types of FAO soil map
HWSD (FAO/IIASA/ISRIC/ISS-CAS/JRC, 2012)	30″	GFDL ESM	GFDL LM4 (Zhao et al., 2018b)	Soil texture classes
HWSD (FAO/IIASA/ISRIC/ISS-CAS/JRC, 2012)	30″	HadCM3 HadGEM2 QUEST	JULES/MOSESvn 5.4 (Best et al., 2011;Clark et al., 2011)	Soil texture
HWSD (FAO/IIASA/ISRIC/ISS-CAS/JRC, 2012)	30″	CNRM-CM5	SURFEX8.1 (Moigne,2018)	Soil texture,soil organic matter
IGBP-DIS (Global Soil DataTask, 2000)	5′	CESM CCSM CMCC–CESM FIO-ESM FGOALS (s2,gl,g2) NorESM1	CLM 3.0 or CLM 4.0 or CLM 5.0 (Oleson, 2013)	Soil texture (sand, clay)
ISRIC-WISE (Batjes, 2006) combined with NCSD (Hugelius et al., 2013)	5′; 0.25°	CESM CCSM CMCC–CESM FIO-ESM FGOALS (s2,gl,g2) NorESM1	CLM 3.0 or CLM 4.0 or CLM 5.0 (Oleson, 2013)	Soil organic matter

Lawrence and Chase (2007)	0.05°	CESM CCSM CMCC–CESM FIO-ESM FGOALS (s2,gl,g2) NorESM1	CLM 3.0 or CLM 4.0 or CLM 5.0 (Oleson, 2013)	Soil color class
Reynolds et al. (2000)	5′	GLDAS	Mosaic (Koster and Suarez, 1992) CLM2 Noah (Chen and Dudhia, 2001) VIC (Liang et al., 1994)	Soil texture classes
Webb et al. (1993) and Zöbler (1986)	1°	GISS-E2	GISS-LSM (Rosenzweig and Abramopoulos, 1997)	Soil texture
Wilson and Henderson-Sellers (1985)	1°	HadCM3 HadGEM2 QUEST	JULES/MOSESvn 5.4 (Best et al., 2011;Clark et al., 2011)	Soil texture
Zöbler (1986)	1°	ACCESS-ESM	CABLE2.0 (Kowalczyk et al, 2013)	Soil texture classes
Zöbler (1986)	1°		SiB (Sellers et al., 1996; Gurney et al., 2008)	Soil texture classes
Zöbler (1986)	1°	CFSv2	CFSv2/Noah(Saha et al., 2014)	Soil texture
Zöbler (1986)	1°	CSIRO-Mk3.6.0	CSIRO-Mk3.6.0 (Rotstayn et al., 2012)	Soil texture classes
Zöbler (1986)	1°	MIROC (4h,5) MIROC-ESM	MATSIRO (Takata et al., 2003)	Soil texture classes

Zöbler (1986); Reynolds et al. (2000)	1°; 5′	IPSL-CM6	ORCHIDEE [rev 3977] (Krinner, 2005)	Soil texture classes

ACCESS = Australia Community Climate and Earth System Simulator
BATS = Biosphere-Atmosphere Transfer Scheme
BCC_CSM = Beijing Climate Center Climate System Model
BCC_AVIM = Beijing Climate Center Atmosphere and Vegetation Interaction Model
BNU_ESM = Beijing Normal University Earth System Model
CABLE = Community Atmosphere Biosphere Land Exchange
CanESM = Canadian Earth System Model
CAS_ESM = Chinese Academy of Sciences Earth System Model
CCSM = Community Climate System Model.
CESM = Community Earth System Model
CFS = Climate Forecast System
CLASS = Canadian Land Surface Scheme
CLM = Community Land ModelCMCC–CESM = Euro-Mediterranean Centre on Climate Change Community Earth System Model
CNRM-CM = Centre National de Recherches Meteorologiques Climate Model
CoLM = Common Land Model
CSIRO-Mk = Commonwealth Scientific and Industrial Research Organization climate system model
CTEM = Canadian Terrestrial Ecosystem Model
EC-EARTH = European community Earth-System Model
FAO = the Food and Agriculture Organization (FAO-UNESCO) digital Soil Map of the World (SMW) at 1:5 million scale
FGOALS = Flexible Global Ocean-Atmosphere-Land System Model
FIO-ESM = The First Institute of Oceanography Earth System Model
GRAPES = Global/Regional Assimilation Prediction System
GFDL = Geophysical Fluid Dynamics Laboratory
GISS = Goddard Institute for Space Studies
GLDAS = Global Land Data Assimilation System
GSDE = Global Soil Dataset for Earth System Model
HadCM = Hadley Centre Coupled Model

HadGEM2-ES = Hadley Global Environment Model 2 - Earth System
HTESSEL = Tiled ECMWF Scheme for Surface Exchanges over Land
HWSD = Harmonized World Soil Database
ICON-ESM = Icosahedral non-hydrostatic Earth System Model
IGBP-IDS = Data and Information System of International Geosphere-Biosphere Programme
IPSL-CM = Institut Pierre Simon Laplace Climate Model
ISRIC-WISE = World Inventory of Soil Emission Potentials of International Soil Reference and Information Centre
JSBACH = Jena Scheme of Atmosphere Biosphere Coupling in Hamburg
JULES/MOSES= Joint UK Land Environment Simulator/Met Office Surface Exchange Scheme
MATSIRO = Minimal Advanced Treatments of Surface Interaction and Runoff
MIROC = Model for Interdisciplinary Research on Climate
MPI-ESM = The Max Planck Institute for Meteorology Earth System Model
Noah-MP = Noah-multiparameterization
NorESM1 =
NCSD = Northern Circumpolar Soil Carbon Database
ORCHIDEE = Organising Carbon and Hydrology In Dynamic Ecosystems
QUEST = Quantifying and Understanding the Earth System
RegCM = Regional Climate Model
SiB = Simple Biopshere Model
STATSGO = the State Soil Geographic Database
SURFEX = Surface Externalisée
WRF = Weather Research and Forecasting Model

Table 2 Four new global soil datasets for the updates of ESMs.

Dataset*	Resolution	Number of layers	Number of properties	depth to the bottom of a layer (cm)	Mapping method
HWSD	1km	2	22	30, 100	Linkage method
GSDE	1km	8	39	0, 4.5, 9.1, 16.6, 28.9, 49.3, 82.9, 138.3, 229.6	Linkage method
WISE30sec	1km	7	20	20,40,60,80,100,150,200	Linkage method
Soilgrids	250m	6	7	5, 15, 30, 60, 100, 200	Digital soil mapping

*HWSD, GSDE, WISE30sec and Soilgrids are freely available at http://www.iiasa.ac.at/web/home/research/researchPrograms/water/HWSD.html, http://globalchange.bnu.edu.cn/research/data, https://www.isric.org/explore/wise-databases, and http://www.soilgrids.org/, respectively.

Table 3 Derived soil properties considered in Four global soil datasets.

Soil property*	HWSD	GSDE	WISE30sec	Soilgrids	Soil property*	HWSD	GSDE	WISE30sec	Soilgrids
Drainage class	√	√	√		Total carbon		√		
AWC class	√	√			Total nitrogen		√	√	
Soil phase	√	√			Total sulfur		√		
Impermeable layer	√	√			pH(KCL)		√		√
Obstacle to roots	√	√			pH($Cacl_2$)		√		
Additional property	√	√			Exchangeable Ca		√		
Soil water regime	√	√			Exchangeable Mg		√		
Reference soil depth	√	√			Exchangeable K		√		
Depth to bedrock				√	Exchangeable Na		√		
Gravel	√	√	√	√	Exchangeable Al		√		
Sand, Silt, Clay	√	√	√	√	Exchangeable H		√		
Texture class**	√				VWC at -10 kPa		√		
Bulk density	√	√	√	√	VWC at -33 kPa		√	√	
Organic Carbon	√	√	√	√	VWC at -1500 kPa		√	√	
pH(H_2O)	√	√	√	√	Phosphorous by Bray method		√		
CEC (clay)	√		√		Phosphorous by Olsen method		√		
CEC (soil)	√	√	√		Phosphorous by New Zealand method		√		
Effective CEC			√		Water soluble phosphorous		√		
Base saturation	√	√	√		Phosphorous by Mechlich method		√		

TEB	√		√	Total phosphorous		√	
Calcium Carbonate	√	√	√	Total Potassium		√	
Gypsum	√	√	√	Salinity (ECE)	√	√	√
Sodicity (ESP)	√		√	Aluminium saturation			√
C/N ratio			√				

*CEC is cation exchange capacity. The base saturation measures the sum of exchangeable cations (nutrients) Na, Ca, Mg and K as a percentage of the overall exchange capacity of the soil (including the same cations plus H and Al). TEB is total exchangeable base including Na, Ca, Mg and K. ESP is exchangeable sodium percentage, which is calculated as Na*100/CECsoil. ECE is electrical conductivity. AWC is the available water storage capacity. The first 9 soil properties on the left including drainage class, AWC class and so on are available for soil types, while the other properties are available for each layer. It should be noted that many different analytical methods have been used to derive a given soil property, which is a major source of uncertainty.

**texture class can be calculated using sand, silt and clay content

Table 4 Evaluation statistics of soil datasets using WoSIS soil profiles. ME is mean error. RMSE is root mean squared error. CV is coefficient of variation. R^2 is coefficient of determination.

Soil property	Dataset	Topsoil (0-30 cm)				Subsoil (30-100 cm)			
		ME	RMSE	CV	R^2	ME	RMSE	CV	R^2
Sand content (% in weight)	Soilgrids	-0.906	18.6	0.457	0.518	-0.269	19.1	0.501	0.492
	GSDE	-0.443	23.2	0.571	0.247	-1.31	23.8	0.625	0.211
	HWSD	6.64	27.4	0.673	0.014	2.08	27.6	0.725	-0.0575
	IGBP	3.74	26.3	0.647	0.0514	4.06	26.3	0.691	0.0546
Clay content (% in weight)	Soilgrids	1.34	12.5	0.554	0.339	0.386	13.6	0.485	0.382
	GSDE	-0.949	14.6	0.643	0.104	-0.794	16.4	0.584	0.105
	HWSD	0.77	16.2	0.718	-0.119	1.42	18.9	0.672	-0.182
	IGBP	3.27	15.4	0.678	0.0444	2.44	16.8	0.597	0.0841
Bulk density (kg/m3)	Soilgrids	-79.7	237	0.164	0.338	-33.5	212	0.136	0.327
	GSDE	-68.4	279	0.193	0.0303	-65.5	269	0.173	-0.043
	HWSD	-105	298	0.206	-0.033	-168	317	0.204	-0.107
	IGBP	-55.6	273	0.189	0.0499	-112	294	0.189	-0.13
Coarse fragment (% in volume)	Soilgrids	1.53	10.1	1.68	0.319	1.23	12.8	1.47	0.335
	GSDE	3.2	13.5	2.24	-0.165	3.18	16.8	1.93	-0.115
	HWSD	1.8	13.2	2.2	-0.164	-0.401	16.2	1.87	-0.0805
	IGBP	-100	-100	-100	-100	0.99	23.5	3.32	0.134
Organic carbon (g/kg)	Soilgrids	6.21	29.8	1.69	0.218	0.45	27.4	3.87	-0.174
	GSDE	-0.354	34.5	1.95	-0.095	-1.38	27.4	3.87	-0.172
	HWSD	-3.67	36.2	2.05	-0.194	1.67	28.5	4.02	-0.268
	IGBP	0.605	33.4	1.89	-0.026	-0.269	19.1	0.501	0.492

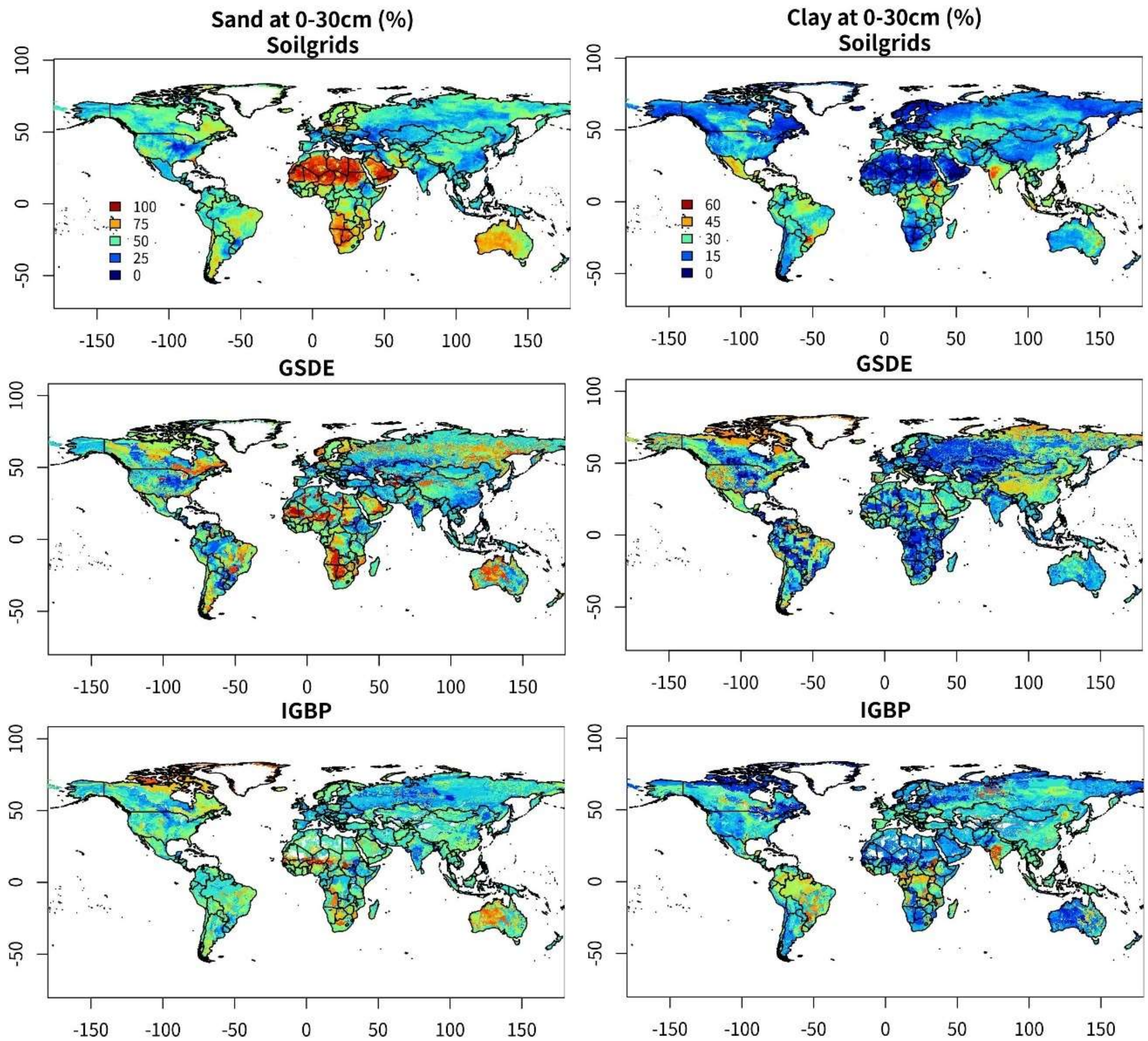

Figure 1 Soil sand and clay fraction at the surface 0-30 cm layer from Soilgrids, IGBP-DIS and GSDE. The difference among them will lead to different modeling results for ESMs. IGBP-DIS is Data and Information System of International Geosphere-Biosphere Programme, and GSDE is Global Soil Dataset for Earth System Model.

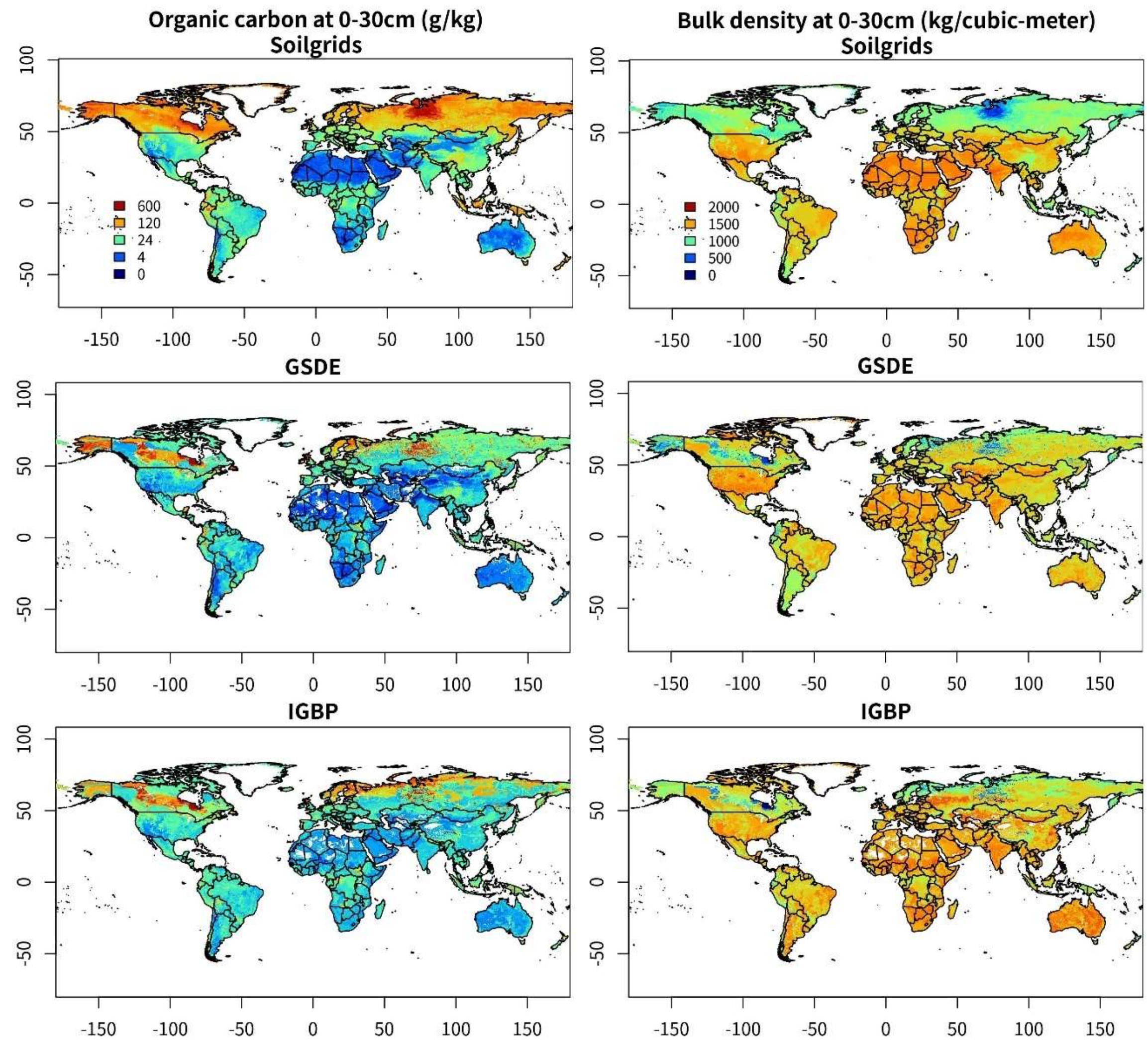

Figure 2 Soil organic carbon and bulk density at the surface 0-30 cm layer from Soilgrids, GSDE and IGBP.

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