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THE VARIABILITY OF SOIL ORGANIC CARBON POOL AND THE POTENTIAL OF GROUND PENETRATING RADAR IN ITS ESTIMATING

Variabilita zásob uhlíku v půdě a možnost využití GPR radaru k jejich zjišťování

Doctoral thesis

Supervisor: RNDr. Tomáš Chuman, Ph.D.

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Prohlašuji, že jsem závěrečnou práci zpracovala samostatně a že jsem uvedla všechny použité informační zdroje a literaturu. Tato práce ani její podstatná část nebyla předložena k získání jiného nebo stejného akademického titulu.

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podpis

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Abstract

In the context of ongoing climate change, more attention is being given to soil and its organic carbon pool. This is because soil could partially compensate for the increasing amount of carbon dioxide in the atmosphere or, on the other hand, be a vast pool of carbon dioxide if organic matter stored in soil mineralizes. Therefore, the precision of soil organic carbon pool estimation, development of monitoring methods, and revelation of factors controlling the pool have been more and more focused on by soil scientists. Conventional soil sampling for soil organic carbon pool estimation and modelling includes manual sampling, measuring forest floor depth and bulk density, and taking soil samples for carbon concentration analysis. These are time and labour demanding. Therefore, there is an effort to develop precise models predicting the carbon pool based on its driving factors that would limit the amount of fieldwork. The models often use remote sensing data, and, in addition, there is an effort to estimate soil organic carbon concentration from soil spectral characteristics.

Nevertheless, another variable needed to estimate the organic carbon pool is the thickness of the soil profile or individual soil horizons. The thickness can hardly be determined from remote sensing data, so it has to be measured in the field. However, some geophysical methods look promising and could provide thickness information in greater detail and with less effort than manual sampling; in particular there is ground-penetrating radar, which is being engaged to estimate the horizon depths non-destructively.

This doctoral thesis aims to bring new knowledge about the soil organic carbon pool, factors controlling the pool, and methods for estimating it in temperate forests. It examines the variability of the soil organic carbon pool and its driving factors and, subsequently, the variability of forest floor and topsoil thicknesses and their driving factors. However, the main objective was to test the usability of ground-penetrating radar to estimate forest floor and topsoil thicknesses.

The soil organic carbon pool was analyzed along several gradients across the Czech Republic. The forest floor and topsoil thicknesses were studied at a finer scale at a site of 1 km^2. Both studies examined the effect of climatic conditions, vegetation, anthropogenic acid deposition, and other factors on the soil organic carbon pool and the forest floor and topsoil thicknesses. The potential of ground-penetrating radar for soil survey was reviewed, based on 130 articles published on the Web of Science and

SCOPUS between 1995 and 2018. The review summarizes approaches, purposes, and conditions of ground-penetrating radar use in soil surveying. The fieldwork comprises ground-penetrating radar surveys of organic layer depths, repeatedly run on the same transects on two study sites with contrasting soil types under different moisture conditions. Ground-penetrating radar outputs were verified with the actual depth measured manually at the field.

The study of the driving factors of soil organic carbon pool and forest floor and topsoil thicknesses found that climatic conditions, vegetation, and acid deposition controlled the soil organic carbon pool and the forest floor and topsoil thicknesses at both scales (regional acrros the Czech Rpublic and local at 1 km^2 site). The best predictors, however, differed between scales. An approach to data processing was proposed to estimate forest floor and topsoil thicknesses using ground-penetrating radar. The approach did not detect the boundary between the forest floor and topsoil, but it was successful for the topsoil/mineral soil boundary. The average error of thickness estimation was about 25%. However, the mean thickness at the transects applicable for soil organic mass estimation showed a mean measurement error of only up to about 9%. Average measurement errors were slightly lower under wetter conditions, but the mean thickness estimation was more accurate under the driest conditions.

Key words: soil organic carbon pool, ground-penetrating radar, forest floor thickness, topsoil thickness, moisture conditions

Abstrakt

V souvislosti s probíhající klimatickou změnou zapříčiněnou zejména růstem oxidu uhličitého v atmosféře, je stále více pozornosti věnováno výpočtu organického uhlíku v půdě a možnostem jeho sekvestrace. Půda je největším terestrickým zásobníkem uhlíku a může zpomalovat stoupající množství oxidu uhličitého v atmosféře jeho sekvestrací nebo v opačném případě být významným zdroje oxidu uhličitého, pokud by došlo k mineralizaci organického uhlíku uloženého v půdě. Proto se pedologie stale více zabývá zpřesňováním odhadů uhlíkových zásob, vývojem metod jejich monitorování a hledáním faktorů, které sekvestraci a stabilizaci uhlíku v půdě ovlivňují. Konvenční sběr dat za účelem odhadů zásob uhlíku v půdě sestává z manuálního terénního průzkumu pomocí půdních sond, měření mocností horizontů a odběru vzorků pro stanovení obsahu organického uhlíku. Tyto práce jsou však časově i finančně značně náročné. Proto je snahou nalézt faktory, které zásobu organického uhlíku ovlivňují a na jejich základě predikovat množství uhlíku v místech, kde půdní průzkum nebyl proveden. Významný posun přinesl i dálkový průzkum země, který umožňuje odhadovat koncentraci půdního organického uhlíku na základě spektrální odrazivosti půdy. Nicméně, jedním z klíčových parametrů potřebných pro odhad zásob uhlíku v půdě je mocnost půdního profilu (jednotlivých horizontů), kterou však lze jen velmi obtížně určit pomocí dákového průzkumu, a musí být měřena v terénu. Usnadnění terénních prací slibují některé geofyzikální metody, především georadar (GPR radar), který je určen k měření hloubek bez narušení povrchu a mohl by poskytnout data o mocnostech půdních horizontů ve větším detailu a s menšími náklady.

Předkládaná disertační práce si klade za cíl přispět k poznání zásob organického uhlíku v půdě a faktorů, které je ovlivňují a dále ověřit metodu měření mocnosti půdních horizontů pomocí georadaru v temperátních lesích.

Zásoby uhlíku v půdě byly zkoumány na regionální úrovni celé České republiky, mocnost humusových horizontů byla zkoumána detailněji v rámci jednoho povodí o rozloze 1km^2. Studie na obou úrovních hodnotily vliv klimatických podmínek, vegetace, kyselé atmosférické depozice síry a dusíku a dalších faktorů na zásobu uhlíku v půdě a mocnost humusových horizontů. Vlastní aplikaci georadaru v půdním průzkumu předcházela rešerše na základě 130 článků publikovaných mezi roky 1995-2018 na Web of Science a SCOPUS. Následný výzkum měření mocnosti humusových horizontů radarem GPR probíhal opakovaně za odlišných vlhkostních podmínek na

dvou lokalitách s kontrastními půdními typy a výstupy byly porovnávány s mocnostmi naměřenými manuálně v terénu.

Na obou studovaných úrovních byl zjištěn vliv klimatu, vegetace a kyselé atmosférické depozice síry na zásoby uhlíku v půdě a mocnost humusových horizontů, ale lišily se proměnné, které daný faktor vhodně charakterizovaly. Za účelem zjišťování mocnosti humusových horizontů pomocí GPR radaru byl navržen nový postup zpracování radarových dat, s jehož pomocí bylo detekováno rozhraní humusových horizontů a minerální půdy. Průměrná chyba měření mocnosti se pohybovala kolem 25%, ale průměrná mocnost na celém měřeném transektu vykazovala chybu jen do 9 %. Průměrná chyba měření mocnosti byla mírně nižší za vlhčích podmínek, ale odhad průměrné mocnosti byl nejpřesnější za nejsušších podmínek.

Klíčová slova: zásoby uhlíku v půdě, radar GPR, mocnost nadložního humusu, mocnost organominerálního horizontu, vlhkostní podmínky

List of publications included in the doctoral thesis

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Publication I: KZ contributed to data processing and manuscript writing. Author's contributions: 10%

Publication II: KZ performed the fieldwork, analysed data, and contributed to manuscript writing. Author's contributions: 70%

Publication III: KZ performed the literature review and contributed to manuscript writing. Author's contributions: 70%

Publication IV: KZ performed fieldwork and contributed to manuscript writing. Author's contributions: 70%

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RNDr. Tomáš Chuman, Ph.D.

CONTENTS

List of Tables

List of Figures

1. Introduction

In the context of ongoing climate change, the attention paid to soil organic carbon is increasing because soils act as an essential long-term carbon sink. The soil organic carbon pool is several times larger than the atmospheric pool; thus, soils could compensate for the increasing amount of carbon dioxide in the atmosphere or, on the other hand, be a vast pool of carbon dioxide if organic matter in soil mineralizes (Lal, 2004). Therefore, numerous soil surveys and studies have focused on the accuracy of soil organic carbon pool estimation and monitoring its changes in all environments, from tropical forests (e.g., Rossi et al., 2009), desserts and semi-desserts (e.g., Brahim et al., 2014), to subtropical vegetation (e.g., Conforti et al., 2016; Francaviglia et al., 2017), temperate forests (e.g., Ahmed et al., 2016; Cremer et al., 2016; Marty et al., 2015; Schöning et al., 2006), and boreal forests (e.g., Hansson et al., 2013; Kristensen et al., 2015; Marty et al., 2015; Strand et al., 2016). Special attention has been paid to forests because they store large amounts of organic carbon in their biomass and soil, mainly in the forest floor (organic horizons). The proportion of organic carbon in soils from the whole ecosystem pool increases from the equator to the poles, reaching 60% in boreal forest soils (Pan et al., 2011).

Models of soil organic carbon pools calculate the soil organic carbon stock using carbon concentration in soil, soil bulk density, and soil/soil horizon thickness. Thus, at middle and larger scales, the models require a large number of soil samples for the determination of carbon concentration, bulk density, and the thickness of soil horizons. Conventional soil sampling is time and labour demanding; therefore, there is an effort to develop models predicting soil organic carbon stocks based on easily available data to predict soil organic carbon stocks precisely, also in areas where field data are missing or scarce. These models often employ remote sensing data showing land use, vegetation and its state; however, soil properties such as bulk density, organic carbon concentration, texture, and soil depth are hard to determine from remote sensing data (Sothe et al., 2022). Even if some studies try to estimate soil organic carbon concentration based on hyperspectral airborne data calibrated using near-infrared laboratory measurements (Hong et al., 2020), this method is not applicable on land with dense vegetation or canopies. Therefore, most methods of organic carbon stocks estimation using remote sensing data (e.g. vegetation cover) combine it with several datasets (such as climatic data or existing soil types and geology maps) and predict the soil organic carbon pool based on its relation to these variables (e.g., Gardin et al., 2021; Sothe et al., 2022). Thus, there is still an urgent need to find factors that drive soil organic carbon sequestration and stock (Tab. 1), and that could thus serve for organic carbon pool estimation and predicting its changes. The factors are known at the global level, but they differ at the regional and local levels. Studies that work with local factors show better predictions of the organic carbon pool (e.g., Aitkenhead and Coull, 2020).

Still, one of the crucial variables needed to estimate the organic carbon pool is soil profile depth or depth of individual soil horizons. Depth is hard to determine from remote sensing data (Sothe et al., 2022). Therefore, depth has to be measured in the field. There is a growing effort to apply geophysical methods in horizon thickness estimating to avoid manual field sampling. Ground-penetrating radar was suggested to help with surveys of soil stratigraphy (e.g., André et al. 2012; Nováková et al. 2013; Zhang et al. 2014) and estimating soil organic horizons thicknesses (e.g., Li et al., 2015; Voronin and Savin, 2018; Winkelbauer et al., 2011). The method offers time savings in the field and, more importantly, produces continuous data from transects instead of discrete information from point sampling. Another advantage is the possibility to repeat the measurement at the exact location because the method does not disturb the soil.

This doctoral thesis aims to contribute to soil organic carbon pool estimation and modelling effectiveness. Its objective is to determine whether the factors suggested by previous studies to control soil organic carbon pool (Tab. 1) drive the organic carbon pool in Czech Republic forest soils. The studied factors are climate, elevation, soil moisture, topography, parent material, vegetation, soil type, soil texture, and soil acidification (Tab. 1). Next, the thesis focuses on estimating forest floor and topsoil thicknesses. We study whether forest floor and topsoil thicknesses are affected by the same factors as the organic carbon pool in the mineral soil, and we examine the possibility of using ground-penetrating radar in horizon thicknesses estimation. We further compare ground-penetrating radar measurements performed under different moisture conditions to recommend optimal conditions for such surveys.

2. Background

2.1. Organic carbon on Earth

Carbon on the Earth is dissolved in oceans and freshwaters, dispersed in the atmosphere as carbon dioxide or methane, stored in the soil, builds organic tissues, and is a compound of rocks (Fig. 1). The carbon of organic tissues is called organic carbon. It can be stored in biomass, soils, and the lithosphere as a compound of fossil fuels or dissolved in waters. Organic carbon in living organisms is changed into its inorganic form and released into the atmosphere by biotic oxidation – respiration by plants and animals (Hannah, 2011). Organic carbon in fossil fuels is released into the atmosphere by combustion. From the atmosphere, inorganic carbon (carbon dioxide) is taken up either by the ocean, where it is dissolved in seawater, or by vegetation, that incorporates the carbon dioxide via photosynthesis into the organic tissue of plants as organic carbon again (Hannah, 2011). Residues of plants, containing about 45% organic carbon mass, are partly respired to the atmosphere by soil fauna and microorganisms performing decomposition; they are partly decomposed and humified to a more stable organic form that is stored in soil. From the soil, organic carbon can then be mineralized and released back into the atmosphere (Duchaufour, 1997). In oceans, inorganic carbon from the atmosphere is either uptaken by marine plants, and changed to organic carbon, or sedimented and incorporated into rocks. From the rocks, it can be released by weathering (Hannah, 2011).

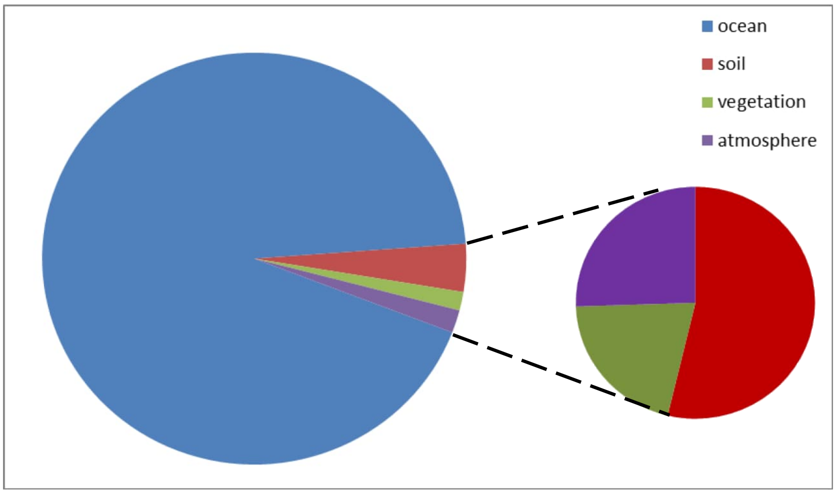

Fig. 1 Organic carbon on Earth

Carbon in the lithosphere is not included because its pool is many times larger than the sum of the other pools

Source: based on data from Hannah (2011)

Thus, organic carbon stored in an ecosystem (vegetation, organisms, and soil) all comes from the atmosphere. However, ecosystems differ in pools of organic carbon and their distributions. Forests store more organic carbon than grasslands. Among them, tropical forests represent the largest terrestrial pool of organic carbon (Fig. 2).

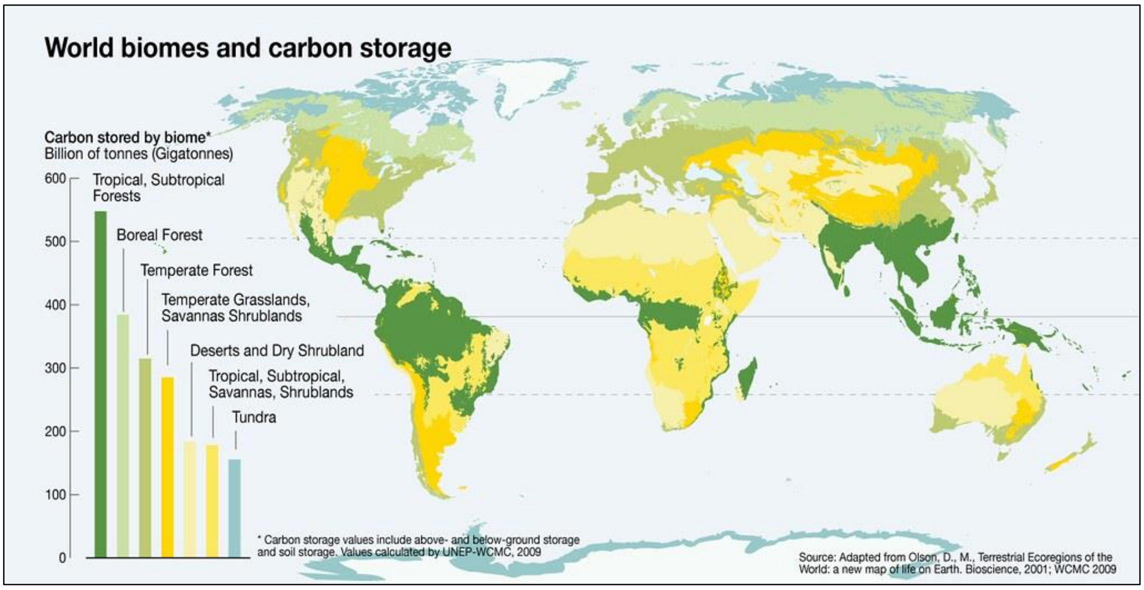

Fig. 2 Organic carbon pool in world biomes

Source: GRIDA, 2015

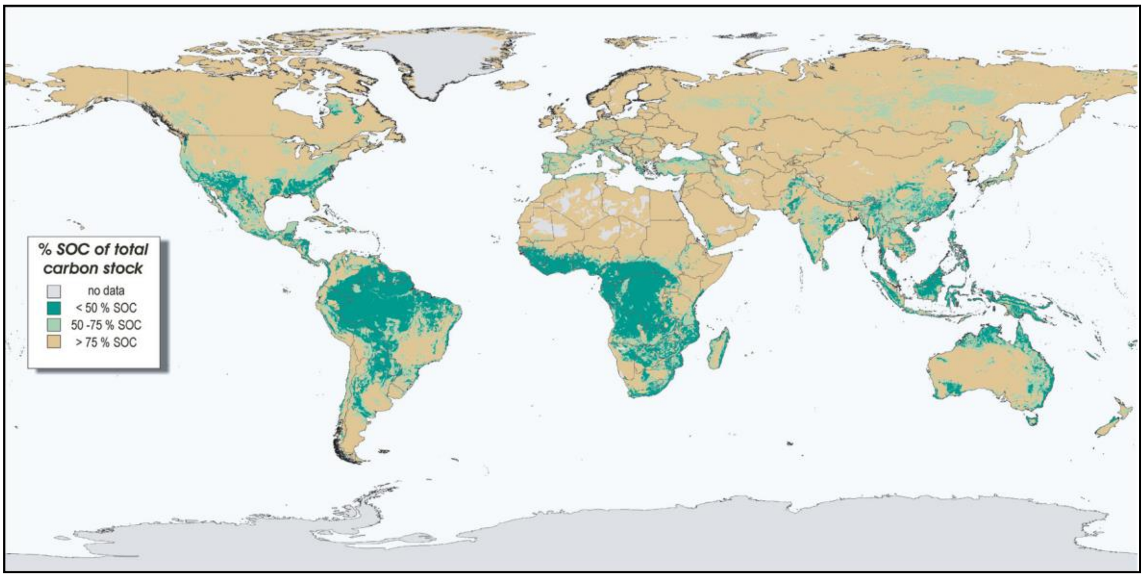

Fig. 3 Proportion of an ecosystem's organic carbon stored in the soil

Source: Scharlemann et al. (2014)

However, grasslands store more organic carbon in mineral soils than forests, where a considerable amount of the carbon is stored in live biomass (Birkenland, 1984; De Kovel et al., 2000), which represents 42% of the total carbon pool in forests (Pan et al., 2011). Another 5% of carbon is stored in the litter, 8% in deadwood, and 44% in the soil to a one-metre depth (Pan et al., 2011). However, the proportion of the organic carbon in soils increases from the equator to the poles (Fig. 3). In tropical forests, 32% of organic carbon is stored in soils, whereas in boreal forests, organic carbon stored in soil represents 60% of the ecosystem pool (Pan et al., 2011).

2.2. Variability of soil organic carbon pool and its modelling

The soil organic carbon pool differs across landscapes. Besides the already mentioned climate and vegetation that drive its diversity, several other factors control the organic carbon pool in soil (Tab. 1).

Tab. 1 Factors driving soil organic carbon stock

Factor	Studies
climate	Jobbágy and Jackson, 2000; Marty et al., 2015; Wiesmeier et al., 2013
elevation	Anschlag et al., 2017; Bojko and Kabala, 2017; Labaz et al., 2014; Marty et al., 2015; Wiesmeier et al., 2013; Zhang et al., 2020
soil moisture	Nicola et al., 2014; Strand et al., 2016
topography	Laamrani et al., 2014a,b; Nicola et al., 2014; Zhang et al., 2020
parent material	Bai and Zhou, 2020; Nicola et al., 2014; Ponge et al., 2011; Schöning et al., 2006
vegetation	Bai and Zhou, 2020; De Kovel et al., 2000; Paz-González et al., 2000; Schulp and Veldkamp, 2008; Wiesmeier et al., 2015
soil type	Bai and Zhou, 2020; Bojko and Kabala, 2017; Brahim et al., 2014; Labaz et al., 2014; Šamonil et al., 2011; Strand et al., 2016
acidification	Mulder et al., 2001; Oulehle et al., 2018, 2008

SOC = soil organic carbon stock

Climate is considered the primary factor globally driving the amount of soil organic matter through its impact on biomass productivity and decomposition rates (Bellamy et al., 2005; Liski et al., 2002). The main climate variables impacting soil organic carbon are temperature and precipitation (Jones, A., Breuning-Madsen, H., Brossard, M., Dampha, A. et al., 2013). In general, higher temperature favours biomass production and its decomposition. Higher precipitation also favours biomass production (Wiesmeier et al., 2019). However, the effect of precipitation on the decomposition is less clear and differs in diverse biomes (Jones, A., Breuning-Madsen, H., Brossard, M., Dampha, A. et al., 2013; Jones et al., 2005). At a finer scale, the climate effect is even less clear, and it depends on the limiting factor in the region (Wiesmeier et al., 2019). In temperate forests, the soil organic carbon pool increases with precipitation and decreases with temperature (Marty et al., 2015; Wiesmeier et al., 2019). Elevation can be a good indicator at a regional and local scale instead of climatic variables (Wiesmeier et al., 2019, 2013). The soil organic carbon pool in temperate forests increases with elevation (Anschlag et al., 2017; Labaz et al., 2014; Marty et al., 2015). A crucial role in soil organic matter accumulation has been attributed to soil moisture. Its effect is similarly complex like the effect of precipitation, and it differs in diverse biomes (Jones, A., Breuning-Madsen, H., Brossard, M., Dampha, A. et al., 2013; Jones et al., 2005; Strand et al., 2016). In temperate forests, high moisture reduces microbial activity due to reduced oxygen availability and, thus, reduced carbon losses via heterotrophic respiration (Nicola et al., 2014; Strand et al., 2016; Wiesmeier et al., 2019). Consequently, high soil moisture enhances soil organic matter accumulation and storage in the forest floor and topsoil. The soil moisture regime is influenced by topography, which forms conditions for water drainage or accumulation (Laamrani et al., 2014,; Nicola et al., 2014; Wiesmeier et al., 2019). Lower slopes and concave sites encourage water accumulation, whereas steep slopes and convex sites enhance water runoff.

Other environmental factors controlling soil organic matter accumulation and storage act mainly at local scales, and they comprise parent material, vegetation, and soil type. Parent material is projected mainly to soil physical properties, such as soil texture and bulk density, and chemical properties, including soil acidity. These soil properties control water retention, biomass production, and decomposition rate (Nicola et al., 2014; Ponge et al., 2011; Schöning et al., 2006; Wiesmeier et al., 2019). In addition, soil organic matter in well-drained soils is held thanks to its association with minerals with large specific surface areas, especially clays and iron and aluminium oxides and hydroxides (Caravaca et al., 1999; Grand and Lavkulich, 2011; Spielvogel et al., 2008).

Vegetation drives soil organic matter accumulation and storage through biomass production and decomposability differences (Marty et al., 2015). The soil organic carbon pool in the forest floor and topsoil is higher under coniferous trees due to their acidic and recalcitrant litter (Cremer et al., 2016; Marty et al., 2015; Strand et al., 2016; Wiesmeier et al., 2019). The average forest floor/topsoil thicknesses under the most studied temperate and boreal forest tree species are shown in Tab. 2.

Tab. 2 Forest floor thickness under the most studied temperate tree species

Dominant tree species	Thickness [cm]	Stand age [years]	Studies
Spruce *Picea abies or Picea mariana*	4.7	188	*Kristensen et al. 2015*
	6.7	50	*Hansson et al. 2013*
	8.1	182	*Kristensen et al. 2015*
	8.4	mixed	*Labaz et al., 2014*
	19 - 21	mixed	*Yu et al. 2002*
Pine *Pinus sylvestris or Pinus banksiana*	2	young	*Yu et al. 2002*
	4.2	100 - 130	*Liski 1995*
	4.7	50	*Hansson et al. 2013*
	5 - 7	middle - old	*Yu et al. 2002*
	8	70	*Smit 1999*
	10.7	84	*Bens et al. 2006*
Aspen *Populus tremula or Populus tremuloides*	3.8; 5.6; 7.4	35-70	*Fons et al., 1998*
	9 - 10	mixed	*Yu et al. 2002*
European Beech *Fagus sylvatica*	1 - 4	113	*Schoning et al. 2006*
	3.4	mixed	*Labaz et al. 2014*
	3 - 5	not specified	*Conforti et al. 2016*
	6.4	91	*Bens et al. 2006*
Silver Birch *Betula pendula*	2.1	50	*Hansson et al. 2013*

Forest floor and topsoil thicknesses and their soil organic carbon stock change with forest age; the production of litter by young trees is low, and it increases with age (Bens et al., 2006; Peltoniemi et al., 2004; Pregitzer and Euskirchen, 2004; Strand et al., 2016; Yu et al., 2002). Simultaneously with growth, trees raise their carbon uptake. Consequently, the forest floor and topsoil thicknesses and their carbon pool reach their minimum at an age of 20 years and subsequently rise till the age of 120 years, when litter production slows down (Peltoniemi et al., 2004). At the same time, litter decomposability decreases with tree ageing because the concentration of recalcitrant lignin increases in the litter (Trap et al., 2013). Besides litter production, plant roots also contribute to organic matter accumulation (Ahmed et al., 2016; Smit, 1999). In addition, understory vegetation can change organic matter inputs to soil, pH of the stand, and then biological activity in the soil. It can significantly influence the forest floor and topsoil thicknesses and their carbon stocks (Bens et al., 2006; Hansson et al., 2013; Smit, 1999; Valtera et al., 2013).

Stand pH and soil biological activity with an impact on soil organic carbon pool can change under anthropogenic inputs of acidifying compounds of sulphur or growth-limiting nutrient nitrogen (Moldan et al., 2006; Oulehle et al., 2008). Lowered soil pH favours soil fungi at the expense of soil bacteria (Oulehle et al., 2018) and allows mobilisation of Al^{3+}, which is toxic for plant roots (de Wit et al., 2010). The result is enhanced soil organic matter accumulation (Mulder et al., 2001). Acidification induced by human activity is caused by the deposition of sulphur and nitrogen originating in the combustion of fossil fuels. In central Europe, it is more important in the highlands (Kopáček and Posch, 2011). Increased nitrogen in soil favours biomass production and slows its decomposition (Berg and Matzner, 1997; Hobbie, 2008; Janssens et al., 2010; Liu and Greaver, 2010; Waldrop et al., 2004). Thus, higher nitrogen and sulphur contents lead to greater thicknesses of the forest floor and increase its organic carbon pool (Mulder et al., 2001; Oulehle et al., 2008).

Factors controlling the soil organic carbon pool are the same as those controlling soil-forming processes leading to pedogenesis of various soil types (Jones, A., Breuning-Madsen, H., Brossard, M., Dampha, A. et al., 2013; Jones et al., 2005). Thus, soil types differ in their characteristics (e.g. forest floor thickness). Several studies show differences in the soil organic carbon pool per the soil types (e.g., Brahim et al., 2014; Labaz et al., 2014; Šamonil et al., 2011; Strand et al., 2016). In forest soils of Central Europe, Šamonil et al. (2011) suggested that forest floor plus topsoil in Gleysols reach a thickness of 27.6 cm, in Stagnosols 16.6 cm, in Albic Podzols 13.7 cm, in Entic Podzols 12.9 cm, in Haplic Cambisol 12.3 cm, and in Dystric Cambisol 11.2 cm. However, there is high variability between soil types, and direct comparisons are impossible. In addition, even the same soil types differ in, for example, forest floor thicknesses under different vegetation cover.

Overall, thanks to various factors, there is very high spatial variability of soils and their properties, for example floor thickness (Bens et al., 2006; Kristensen et al., 2015; Liski, 1995; Šamonil et al., 2011; Valtera et al., 2013) and/or carbon pool (Conforti et al., 2016; Heim et al., 2009; Marty et al., 2015; Muukkonen et al., 2009; Rossi et al., 2009; Schöning et al., 2006). That is why precise soil organic carbon pool estimation based on conventional field sampling would require many well-designed data samplings. Sampling is labour, cost, and time consuming. Therefore, there is an effort to find data acquisition methods and develop models to precisely estimate the soil organic carbon pool with more ease.

Among such parameters that are needed for precise soil organic carbon pool estimation are soil horizon thicknesses or bulk density. These parameters are not reliably detectable from remotely sensed data (Sothe et al., 2022). In recent years, there has been an effort to deploy non-destructive geophysical methods to estimate these parameters. These methods do not disturb the ground, so they allow repeatability of such a survey, especially in case of thickness change determination. However, soils represent a very shallow subsurface from the geophysical perspective; thus, most geophysical methods do not apply to soils. One of several exceptions is ground-penetrating radar. Compared to other earth science disciplines, where ground-penetrating radar is more widely used (such as geology or sedimentology), its application in soil science requires higher resolution, which is demanding for the technical instruments and more precise data processing and interpretation. Ground-penetrating radar has been more or less successfully applied to detect deeper soil horizon boundaries or soil/bedrock boundaries (e.g., André et al., 2012; Nováková et al., 2013; Simeoni et al., 2009; van Dam et al., 2003; van Dam and Schlager, 2000, Doolittle and Butnor, 2009), but only a few studies focused on the detection of forest floor and topsoil (e.g., Li et al., 2015; Voronin and Savin, 2018; Winkelbauer et al., 2011). The results of these studies are, however, promising.

2.3. Principle of ground-penetrating radar

Ground-penetrating radar emits electromagnetic waves via an antenna-transmitter and receives them by an antenna-receiver after their reflection (Fig. 4). The reflections emerge on boundaries with contrasting electromagnetic properties if the antenna resolution (i.e. frequency of emitted electromagnetic waves) is sufficient. A reflection emerges on a boundary if $W \,/\, \frac{v}{f} \leq 0.3$ [m;m/s;Hz] (van Dam et al., 2003), where W = boundary width; v=velocity of electromagnetic waves; f=antenna frequency. Soil surveying commonly uses antennas with frequencies over 500 MHz.

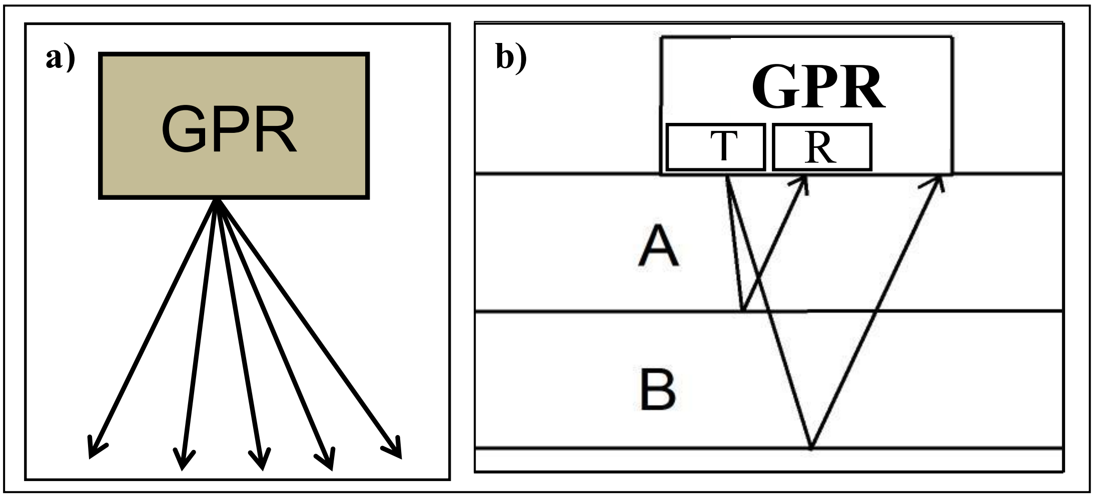

Fig. 4 Ground-penetrating radar principle

a) Ground-penetrating radar (GPR) emitting electromagnetic waves

b) Ground-penetrating radar (GPR) emits electromagnetic waves by antenna-transmitter (T) and receives them back after their reflection by antenna-receiver (R)

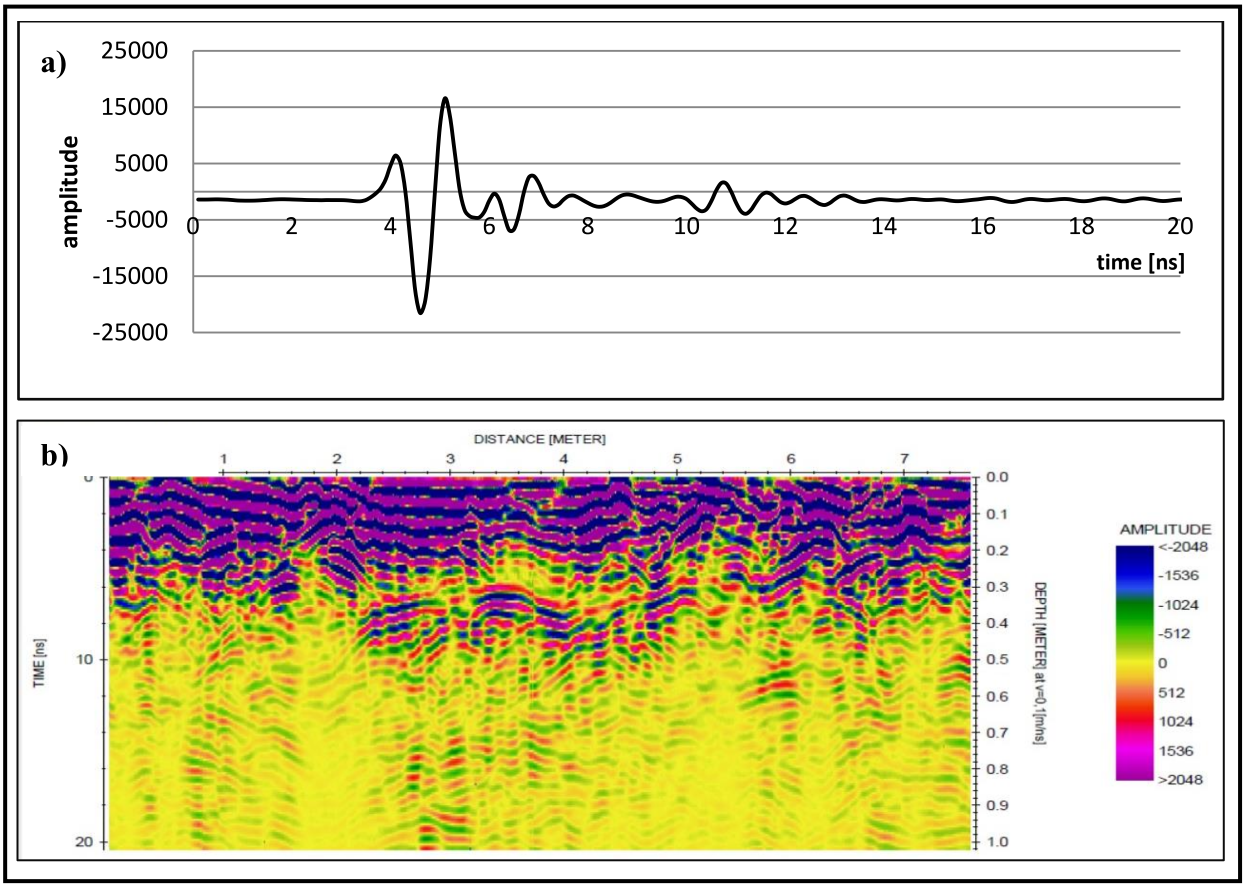

Fig. 5 Common ground-penetrating radar outputs from an Arenic Podzol profile

a) signal response (trace) – unfiltered

b) traces displayed in 2D radargram – filtered by common basic processing steps

A common signal response (trace) consists of the two-way travel times and magnitudes of received reflections (Bristow and Jol, 2003) (Fig. 5a). These outputs are most frequently displayed in 2D radargrams (Fig. 5b) and edited using image processing algorithms, such as those implementing frequency filters to accentuate the reflections. The result is subsequently interpreted by visual expertise, so interpretation is subjective to some extent. More objective approaches are numerical and based on inverse modelling. However, these methods are demanding on technical instruments. They treat data acquired by multi-offset antenna settings, commonly with separated antenna-transmitters and antenna-receivers in various distances (Sena et al., 2008), with multiple antenna-transmitters and antenna-receivers (Buchner et al., 2012), or with broadband antennas with wide frequency bands (e.g., Lambot et al., 2004; Lavoué et al., 2014). To create an image corresponding to the subsurface at a real scale, the two-way travel times have to be recalculated to depth using the velocity of the electromagnetic waves in the soil. Several methods are used to determine electromagnetic wave velocity in the soil. The simplest way from the instrumental perspective is calculation from the two-way travel time of the signal reflected from an object at a known depth (e.g., Ercoli et al., 2018; Goodman et al., 2009; van Overmeeren et al., 1997). However, application in the field can meet some difficulties. Electromagnetic wave velocity can be estimated from soil electromagnetic properties determined by other tools, most often using the time-domain reflectometry principle (e.g. Ardekani et al., 2014; Benedetto, 2010; van Dam et al., 2003, 2002; van Dam and Schlager, 2000). Dielectric permittivity is measured, and the velocity is acquired according to the relation $v = c/\sqrt{\mu\varepsilon}$ (al Hagrey and Müller, 2000; Reppert et al., 2000), where v is electromagnetic wave velocity in a soil; c is electromagnetic wave velocity in a vacuum; ε is dielectric permittivity; and μ is magnetic permeability, which is 1 for most soils. Signal velocity can also be determined from ground-penetrating radar output. The method is performed by matching the shape of hyperbolas originating in a reflection based on the assumption that the wider hyperbola is the higher the velocity is (e.g., Elkarmoty et al., 2017; Olhoeft, 2000).

In addition to 2D images, 3D image models are sometimes employed to provide more detailed interpretations of profile stratigraphy (Bristow and Jol, 2003). The approach is widely used for tree root detection (e.g., Borden et al., 2016; Freeland, 2015; Guo et al., 2013b; Hirano et al., 2009; Li et al., 2016; Liu et al., 2018; Raz-Yaseef et al., 2013; Rodríguez-Robles et al., 2017; Tanikawa et al., 2013; Tardío et al., 2016; Wu et al., 2014; Yeung et al., 2016) and has also been shown to be suitable for soils

(André et al., 2012). However, data collection and processing are much more demanding for 3D models. The data must be acquired along closely spaced parallel lines, or in a grid and then converted into a 3D block model (Bristow and Jol, 2003).

2.4. Effect of conditions on ground-penetrating radar surveying

The strength of the reflection is driven by the difference in electromagnetic properties on the boundary: the more pronounced the difference in electromagnetic properties on the boundary is, the more distinct is the reflection. Two dominant factors of electromagnetic waves spreading in materials are considered to be dielectric permittivity and magnetic permeability, the latter is often ignored due to its occurrence only with ferromagnetic minerals (Cassidy, 2009). The reflectivity on a boundary is defined as $RC = (\sqrt{\varepsilon_{\mathrm{r2}}} - \sqrt{\varepsilon_{\mathrm{r1}}})/(\sqrt{\varepsilon_{\mathrm{r2}}} + \sqrt{\varepsilon_{\mathrm{r1}}})$ (al Hagrey and Müller, 2000; Huisman et al., 2003; van Dam et al., 2003), where RC=reflectivity, and $\varepsilon_{r2,1}$=relative dielectric permittivity of layer one and layer two. The relative dielectric permittivity is dielectric permittivity expressed in values relative to a vacuum. The dielectric permittivity reduces electromagnetic wave velocity and penetration (Cassidy, 2009). The relative dielectric permittivity of most rocks is 3 - 5 (Cassidy, 2009; Conyers, 2012). The relative dielectric permittivity of air is close to 1 (the value in a vacuum), and the highest permittivity, with values reaching 80 - 81, was found in water (Cassidy, 2009; Conyers, 2012). However, Saarenketo (1998) found that permittivity of soil water differs according to how it is stored in the soil. Dielectric permittivity of free water reaches a value of 81, whereas the permittivity of hygroscopic water can be below 4 (Saarenketo, 1998). The permittivity of capillary water is somewhere between these values (Saarenketo, 1998). This fact indicates that water content impacts the dielectric permittivity of soils the most. Therefore, soil moisture estimation is the most frequent application of ground-penetrating in soil surveys applying a wide variety of approaches, as reviewed by Huisman et al. 2003; Slater and Comas 2009; Klotzsche et al. 2018.

Soil profile consists of horizons that differ in soil particle distribution, bulk density, and porosity and are, therefore, supposed to differ in their water content and then in dielectric permittivity. This is the principle assumption to detect soil horizon boundaries and describe soil stratigraphy using ground-penetrating radar. Moreover, other factors determine soil dielectric permittivity in dry soil, for example presence of calcite, bulk density, related porosity and compaction (Salat and Junge, 2010), or soil organic matter content (Jonard et al., 2014; Lauer et al., 2010); this is because dielectric permittivity of organic matter is lower than that of mineral particles. Dry, undecomposed biomass show dielectric permittivity values close to 1; as biomass decomposition increases, the dielectric permittivity increases as well (André et al., 2015; Ardekani et al., 2014; Jonard et al., 2014). The dielectric permittivity of dry organic and organomineral horizons (containing 1.4% volumetric water content) was determined in a laboratory to be ε=1.19 for horizon Oi, ε=3.95 for horizon Oe, and ε=10.3 for Ah horizon (André et al., 2015, 2014). In the field, under more natural conditions of higher moisture (volumetric water content 4.4% for Oi and 13.5–22.8% for Oe), detected values were: ε=2.9 for Oi and ε=6.3 for Oe (André et al., 2016).

In other words, dielectric permittivity of soil consists of dielectric permittivities of its three components: solid (mineral or organic), water, and air, as well as their proportions. There are several models estimating soil dielectric permittivity based on the proportion of the three phases and their permittivities, for example, a complex refractive index method (Birchak et al., 1974) formulated as:

$$\varepsilon = [(\emptyset * S_w * \sqrt{\varepsilon_w}) + ((1-\emptyset) * \varepsilon_m) + (\emptyset * (1-S_w) * \sqrt{\varepsilon_g})]$$

where ε is the dielectric permittivity of the soil; ε_w is the dielectric permittivity of water (=81); ε_m is the dielectric permittivity of the matrix (usually between 3 and 5); ε_g is the dielectric permittivity of air (=1); S_w is water saturation; and ∅ is porosity.

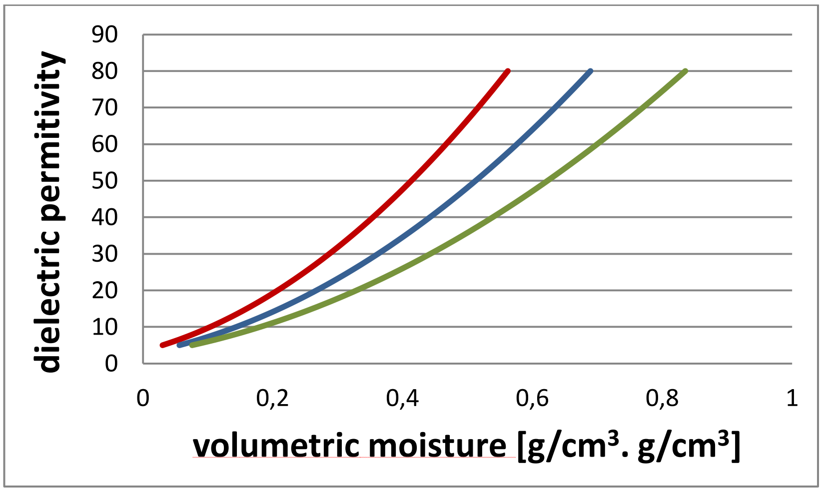

Fig. 6 Relationship of soil dielectric permittivity to soil volumetric moisture modelled by complex refractive index method applied on an example soil

green *– forest floor with 90% porosity;* ***blue*** *– topsoil with 75% porosity,* ***red*** *– subsoil with 63% porosity*

Hypothetically, dry soils could differ in their porosity and/or organic matter content and, as a result, differ in their dielectric permittivities. However, as shown with an example soil modelled using the complex refractive index method (Fig. 6), and as suggested by most studies, a more pronounced difference in dielectric permittivity between soil horizons is achieved under moist conditions (Curioni et al., 2017; van Dam et al., 2002; Zhang et al., 2014) with the conditions of field capacity being optimal, and therefore recommended for ground-penetrating radar survey (van Dam et al., 2002).

3. Aims and objective

This doctoral thesis aims to contribute to soil organic carbon pool estimation and modelling effectiveness. The intention is to determine whether the factors suggested by previous studies (Tab. 1: climate; elevation; soil moisture; topography; parent material; vegetation; soil type; soil texture; and soil acidification) drive soil organic carbon stock at the regional and local level in temperate forests in the Czech Republic, and what factors are the most important. Next, the thesis focuses on estimating forest floor and topsoil thicknesses. We study whether forest floor and topsoil thicknesses are affected by the same factors as the organic carbon pool in a mineral soil, and we test the possibility of using ground-penetrating radar in horizon thicknesses estimation. We further compare the measurements performed under different moisture conditions to recommend optimal conditions for such surveys. The objectives were defined as follows:

I. To determine soil organic carbon pool in the forest floor and different depths of mineral soil down to 80 cm at the regional scale within the Czech Republic and to reveal relationships between soil organic carbon pool and environmental factors, including mean annual temperature, mean annual precipitation, elevation, geology, the proportion of broadleaf trees, forest age, anthropogenic acidification represented by historical sulphur and nitrogen deposition, soil bulk density; and soil texture (publication I).

II. To reveal spatial variability of the forest floor and topsoil thicknesses at a local scale (within a site of 1 km^2) and to examine the relationship between thicknesses and environmental factors. We hypothesize that other variables are important at the local scale next to the factors determined in publication I.

These hypothesized variables included: slope; topography wetness index; dominant tree species; forest age; forest floor cover (needles, leaves, graminoids, moss, bilberries, spruce seedlings); and soil moisture in the subsoil measured in the field (publication II).

III. To review the possibility of ground-penetrating radar application in a soil survey and review the strengths and weaknesses of this method in various soil science applications (publication III).

IV.

a. To use ground-penetrating radar for forest floor and topsoil thicknesses estimation at two forest sites with contrasting soils: Dystric Cambisol and Arenic Podzosol (publication IV).

b. To evaluate the accuracy of the ground-penetrating radar method to estimate forest floor and topsoil thicknesses and its potential in soil organic carbon pool modelling (publication IV).

c. To assess the effect of soil moisture on the accuracy of the measurements (publication IV).

4. Methodology

Most of the surveys were performed within 14 long-term monitored catchments, coordinated by the Czech Geological Survey, across the Czech Republic (Fig. 7). Most of the catchments are covered dominantly by Cambisols (60%) and Podzols (22%) (publication I). The soil organic carbon pool was determined in all catchments (publication I). Thicknesses of forest floor and topsoil were sampled in detail in one of the catchments – Liz (publication II). Subsequently, we surveyed shallow soil stratigraphy using ground-penetrating radar on a shorter transect in the same catchment, and in addition at a locality of Arenic Podzol near the town of Bělá pod Bezdězem in northern Bohemia (publication IV). The ground-penetrating radar survey was designed after we had reviewed 130 papers published on the Web of Science and SCOPUS from 1995 to 2018 (publication III). The keywords were: ground-penetrating radar and soil.

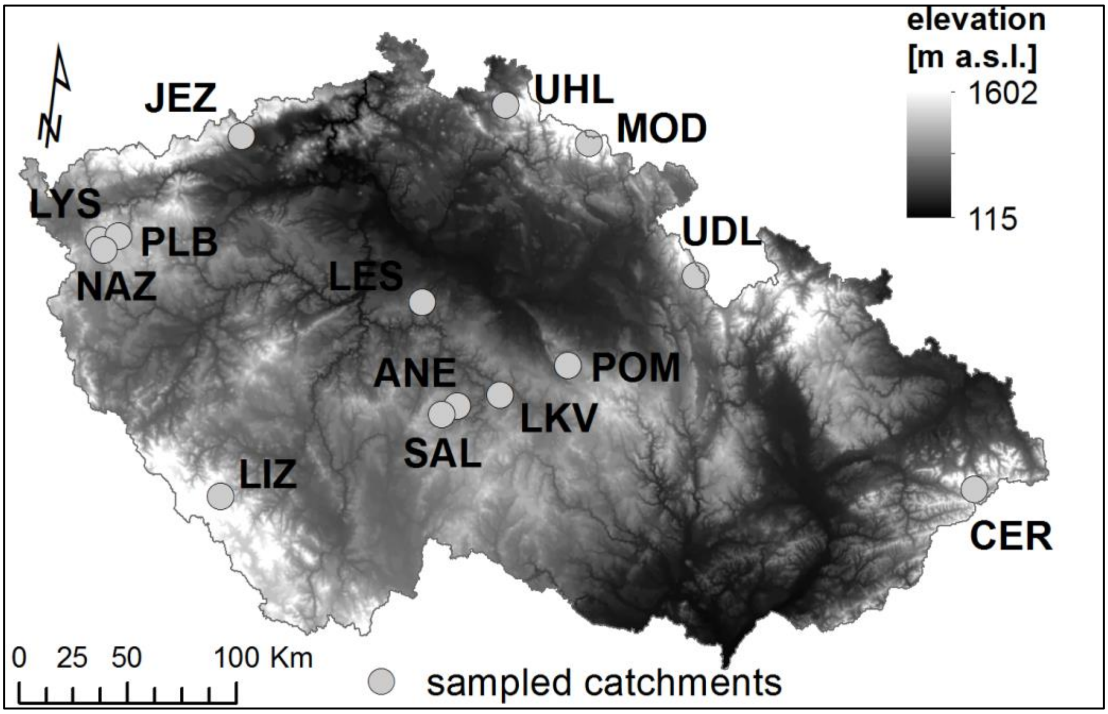

Fig. 7 Localization of long-term monitored catchments used as study sites

Source: Publication I

The soil organic carbon pool was estimated based on quantitative soil pits to a depth of 80 cm in mineral soil within 0.5 m^2. The estimation was calculated from the quantity of forest floor and mineral soil mass separately for forest floor and different depths of mineral soil. The role of environmental factors on soil organic carbon pool size was modelled using a linear mixed-effect model (publication I). The factors included elevation, mean annual temperature, annual precipitation, geochemical reactivity, forest age, proportion of broadleaf trees, and soil texture; because, in recent decades, most of these catchments were exposed to significant nitrogen and sulphur depositions (Oulehle et al., 2017), these variables were also included.

For a detailed analysis, the thicknesses of forest floor and topsoil were measured at soil pits across the Liz catchment. We tried to evaluate their spatial variability and analyse environmental factors affecting thicknesses (publication II). Environmental factors included: soil edaphic category; forest age; dominant tree species; forest floor cover (needles, leaves, graminoids, moss, bilberries, spruce seedlings); topography described by elevation; slope and topography wetness index; and soil moisture in the subsoil. Since the data showed spatial autocorrelation, they were analysed by means of geographically weighted regression (Fotheringham et al., 2002).

Finally, we surveyed forest floor and topsoil thicknesses using a shielded bistatic antenna ground-penetrating radar system–type Ramac by MALÅ Geosciences (Sweden), with an 800 MHz antenna equipped with a wheel-odometer (publication IV). Ground-penetrating radar surveys were repeatedly run on the same transects on two study sites with contrasting soil types; the Dystric Cambisol site in the Liz catchment and the Arenic Podzol site in northern Bohemia near the town of Bělá pod Bezdězem, under different moisture conditions. Time-depth conversion of ground-penetrating radar data was made using velocity of electromagnetic waves calculated from soil dielectric permittivity measured during the survey employing GS3 Soil Moisture Sensor, by Decagon Devices, Inc., working on the principle of capacitance. Ground-penetrating radar data were processed and interpreted in one-dimensional analysis trace by trace. The data was not filtered to better show individual reflections of the ground-penetrating radar signal and their oscillations. The determined point thicknesses were used for detailed reconstruction of the forest floor plus topsoil thickness along the survey transect, and compared with the actual depth measured manually in the field (referred to as point values in the text).

5. Major findings

5.1. The variability of soil organic carbon pool

The soil organic carbon pool of the forest floor was driven mainly by soil acidification and the proportion of broadleaved trees in the forest, together explaining 27% of its variability. In comparison, total soil organic carbon in the whole soil profile was only influenced by elevation, explaining 24% of its variability (Tab. 3). All of these factors increased the soil organic carbon pool. Soil texture mainly influenced the soil organic carbon pool in a mineral soil's shallower depths. Only half of the total soil organic carbon pool down to 80 cm depth of the soil profile was located to the depth of 20 cm in mineral soil, and only 25% was stored in the forest floor. However, the soil organic carbon pool of the forest floor changes significantly with anthropogenic factors, as deduced from the role of acidification and proportion of broadleaved trees. In addition, there was an essential effect of historical acidification on the thickness of the forest floor (Tab. 3, publication I).

Tab. 3 Most important factors controlling soil organic carbon pool and thicknesses of forest floor and topsoil, and percentage of variability explained by these factors or their combinations in models

<table>
<tr><th rowspan="2"></th><th colspan="5">regional scale</th><th colspan="3">local scale</th></tr>
<tr><th colspan="4">organic carbon pool</th><th>thickness</th><th colspan="3">thickness</th></tr>
<tr><th>variable</th><th>forest floor</th><th>mineral soil to 40cm depth</th><th>mineral soil</th><th>total soil</th><th>forest floor</th><th>Oi+Oe horizon</th><th>Oa+topsoil</th><th>forest floor plus topsoil</th></tr>
<tr><td>**elevation**</td><td></td><td></td><td>19</td><td>24</td><td></td><td>0</td><td>0</td><td>0</td></tr>
<tr><td>**soil moisture**</td><td>NS</td><td>NS</td><td>NS</td><td>NS</td><td>NS</td><td>1.3</td><td>6</td><td>5</td></tr>
<tr><td>**acid deposition**</td><td rowspan="2">27</td><td></td><td></td><td></td><td>28</td><td>NS</td><td>NS</td><td>NS</td></tr>
<tr><td>**tree species**</td><td></td><td></td><td></td><td></td><td>1.3</td><td>1.1</td><td>0</td></tr>
<tr><td>**forest floor cover**</td><td>NS</td><td>NS</td><td>NS</td><td>NS</td><td>NS</td><td>10.7</td><td>9</td><td>5.5</td></tr>
<tr><td>**soil texture**</td><td></td><td>27</td><td></td><td></td><td></td><td>NS</td><td>NS</td><td>NS</td></tr>
</table>

values are in% of explained data variability; NS – not studied

Source: results of publication I,II

Thicknesses of forest floor and topsoil show high spatial micro-variability (publication II) in the managed forest, despite the thicknesses being found to be spatially autocorrelated up to 300 m. Spatial autocorrelation explained 7.5% of its overall variability. High variability at the microscale is apparent from the relatively high nugget effect. The ratio of nugget semivariance to sill semivariance did not go under 58.7%. Besides spatial autocorrelation, several factors were found to control thicknesses of the forest floor and the topsoil. Among them, forest floor cover explained 2 - 11% of thickness variability, and soil moisture in the subsoil 2 - 7%. Oi+Oe horizon thickness is controlled mainly by forest floor cover, and Oa+A horizon thickness is controlled by soil moisture (Tab. 3). High soil moisture increases thicknesses; the thicknesses under different forest floor covers are shown in Tab. 4. Characteristics representing topography as slope and topography wetness index had a relatively minor effect. Other tested stand characteristics were not significant, such as elevation, dominant tree species, and stand age (publication II).

Tab. 4 Thicknesses of forest floor and topsoil horizons under different forest floor covers

Forest floor cover		O+A		Oi+Oe		Oa+A	
	N	mean [cm]	*std* [cm]	mean [cm]	*std* [cm]	mean [cm]	*std* [cm]
needles	50	15	*8.4*	3.8	*2*	11.1	*8.1*
needles+moss	54	15.4	*6*	4.6	*2.1*	11.2	*5.7*
moss	37	17.1	*5.8*	5.7	*2.2*	11.4	*5.3*
gramineous plants	9	14.1	*1.2*	4.4	*1.2*	9.7	*1.6*
gramineous plants+moss	12	13.9	*2.2*	4.4	*1.8*	9.5	*2.8*
gramineous plants+needles	2	19.5	*9.5*	2.5	*0.5*	17	*10*
leaves	14	15.3	*5.7*	5.7	*1.9*	9.7	*5.3*
leaves+needles	20	14	*3.9*	5.3	*3*	8.7	*3.2*
bilberries	11	17	*5.5*	6	*1.9*	12	*6.5*
spruce seedlings	12	16	*5.1*	4.5	*2.3*	12	*4.5*

Source: publication II

5.2. Potential of ground-penetrating radar in soil organic carbon pool estimating and effect of soil moisture conditions

Reviewed studies suggest that ground-penetrating radar could aid surveys of soil stratigraphy in significantly layered soils, distinguishing organic and mineral horizons in peats, as well as detecting root systems (publication III). Several studies show its potential to detect forest floor or topsoil in soil profiles (Li et al., 2015; Winkelbauer et al., 2011). Traditional approaches are based on image processing of electromagnetic signals reflected at the boundaries of layers with different electromagnetic properties. These approaches are relatively simple in field measurements and data treatments. However, data processing and interpretation can be quite subjective. Application was relatively successful under favourable conditions, usually including sandy soils; low numbers of other objects, such as stones or dead wood; and the absence of rough surfaces and dense overgrowing vegetation (publication III).

During ground-penetrating radar measurements, either at the Dystric Cambisol site or the Arenic Podzol site (publication IV), the detected uppermost horizon boundary was the boundary between topsoil and mineral soil. The boundary between the forest floor and topsoil was not distinguished. Therefore, forest floor and topsoil thicknesses could not be estimated separately but as one horizon. The average error at the Dystric Cambisol site, with strongly variable topsoil/mineral soil boundary with numerous tree roots and stones, was 25-35%; the average error at the Arenic Podzol site was 18-24%, where tree roots and stones were rare (publication IV). The results show that the thickness of forest floor plus topsoil can be estimated with an error of about 25% using ground-penetrating radar and the suggested one-dimensional analysis. Thickness estimation can be used for soil organic carbon pool modelling. Mean soil thickness at the several metre long transects was determined with an error of up to 9% for the Cambisol site and 8% for the Podzol site. The errors of point values were slightly lower under moister conditions, probably due to a more significant difference in the dielectric permittivity between the horizons. The mean thickness was most accurate under the driest conditions (publication IV). Dielectric permittivity differed less than expected. Despite this limitation, we were able to distinguish the boundary between topsoil and mineral soil.

6. Synthesis and discussion

6.1. The variability of soil organic carbon pool

We studied soil organic carbon pool – the total pool (forest floor and pool down to 80 cm depth of the mineral soil) and separately in different depths of the mineral soil and the forest floor (publication I). We also studied the forest floor thickness (publication II), which is essential for soil organic carbon pool estimation as a substantial carbon pool is stored there. There is a strong correlation between soil organic carbon stored in the horizons (layers) and their thicknesses (e.g., Liski, 1995; Olsson et al., 2009).

The study of soil organic pool variability in publication I was performed at a regional scale, while the study of the forest floor thickness in publication II at a local scale. Both studies conclude very high variability in soil organic carbon pool and forest floor thickness at both scales (publication I, II). Very high variability of forest floor thickness is also confirmed by observations made during the study in publication IV, performed on a micro-scale. Spatial autocorrelation of forest floor and topsoil thicknesses was up to 300 m in a temperate managed forest (publication II), which is significantly more compared to studies in a natural forest, where spatial autocorrelation was only up to 100 m, or 20 m (Šamonil et al., 2011; Valtera et al., 2013). It is probable that the more natural the forest is, the more heterogenous the forest floor is. The impact of higher species heterogeneity on higher spatial autocorrelation was also showed by Bens et al. (2006). Some studies at the micro-scale observed spatial autocorrelation of the forest floor thickness only up to 2 m (Bruckner et al., 1999; Liski, 1995; Muukkonen et al., 2009). As pointed out by Kristensen et al. (2015), scale matters, and it must be kept in mind when comparing studies. For example, studies observed an increased forest floor thickness under trees (Bruckner et al., 1999; Liski, 1995; Muukkonen et al., 2009) at the micro-scale, while there was no relation at a larger scale (Smit, 1999).

Publication I showed elevation as the main factor controlling the total soil organic carbon pool (Tab. 3). Elevation was suggested as a substitute to climatic variables in regional studies (Wiesmeier et al., 2019). Therefore, our findings are in line with previous studies which conclude that higher elevations reduce organic matter decomposition and lead to soil organic carbon accumulation due to lower temperatures and higher precipitations retarding microbial activity (Meier and Leuschner, 2010; Wiesmeier et al., 2013).

Nevertheless, the effect of elevation is amplified by soil acidification because historical sulphur deposition was higher at higher elevations (publication I). Sulphur depositions were accompanied by nitrogen depositions, which were excluded from the analysis due to correlation with sulphur deposition. Increased nitrogen availability favoured biomass production and slowed its decomposition (Berg and Matzner, 1997; Hobbie, 2008; Janssens et al., 2010; Liu and Greaver, 2010; Waldrop et al., 2004). Similarly, increased sulphur concentrations inhibited organic matter decomposition (Oulehle et al., 2018). Thus, higher nitrogen and sulphur content led to greater thicknesses of the forest floor and increased its organic carbon pool (Mulder et al., 2001; Oulehle et al., 2008).

Tree species and forest floor cover are other important factors controlling the carbon pool. The proportion of broadleaf trees was found to drive the carbon pool of the forest floor and upper layers of the mineral soil at a regional scale (publication I), but there was no effect at a local scale (publication II) (Tab. 3). We suggest that it is better substituted by forest floor cover (needles, leaves, graminoids, moss, bilberries, spruce seedlings) at a local scale. Forest floor cover differs between tree species, representing variability of litter inputs and their recalcitrance. Studies by Cremer et al. (2016), Jonard et al. (2017), Labaz et al. (2014), Rothe et al. (2002), Vesterdal et al. (2013, 2008) reported increased forest floor thickness and its carbon pool under coniferous trees compared to broadleaf trees. These results are in line with the results of publication I. However, forest floor and topsoil thicknesses did not differ pronouncedly under forest floor cover of needles and leaves (publication II). The content of recalcitrant lignin in beech litter does not differ from that of spruce under certain conditions (Vesterdal, 1999). Forest floor and topsoil thicknesses were the lowest under graminoids (Tab. 4). Compared with pine needles, lower forest floor thickness under gramineous species was also observed by Bens et al., 2006, and compared to moss and heather by Anschlag et al. (2017). They both argued for better decomposability of gramineous litter. Bastianelli et al. (2017) found thicker soil horizons under moss cover than lichens. They suggested that moss, due to its higher water capacity, forms a water-saturated environment that lowers decomposition rates. Forest floor and topsoil thicknesses increased only slightly under moss in the study catchment of publication II (Tab. 4); however, a relationship of thicknesses to soil moisture measured in subsoil was found (Tab. 3) (publication II). This is in line with low decomposition rates at wet sites previousy discussed. At a local scale, it is appropriate to use soil moisture as a proxy variable representing climate because it expresses micro-climate variability. The elevation suggested as a proxy variable of climate for studies at the regional level (Wiesmeier et al., 2019; results of publication I) was also included in the local study (publication II), but no effect was found.

The effect of the elevation was observed for the total organic carbon pool down to 80 cm depth. In contrast, the soil organic carbon pool in the forest floor was affected only by acidification and the proportion of broadleaf trees (publication I). Similarly, the local study (publication II) showed the most pronounced effect of forest floor cover, expressing vegetation impact on horizon thicknesses. It follows that climate effect on the soil organic carbon pool is most remarkable in deeper parts of the soil profile, which is in line with the findings of Wiesmeier et al. (2013). In the forest floor and topsoil, the effect is masked by anthropic factors, such as land use (Wiesmeier et al., 2013) and acid deposition (Borůvka et al., 2007). The local study (publication II) showed that the thicknesses of Oi+Oe horizons are controlled by forest floor cover, which differs according to forest management and drives litter deposition and its decomposition in the first phases of the decomposition process, while the thicknesses of Oa+A horizons are controlled mainly by soil moisture, slowing organic matter decomposition. It follows that the organic carbon pool in the forest floor and topsoil changes more dynamically. Therefore, the carbon pool of the forest floor and topsoil is essential in monitoring the soil organic carbon pool, despite the forest floor carbon pool representing only 25% of the total soil organic carbon pool (publication I). However, the soil organic carbon pool in deeper horizons/layers should not be omitted from total soil organic carbon pool accounting. It usually represents the most recalcitrant part of the organic carbon pool (Rumpel and Kögel-Knabner, 2011; Schmidt et al., 2011).

6.2. Potential of ground-penetrating radar in soil organic carbon pool estimating

Doolittle and Butnor (2009) reviewed numerous studies of soil stratigraphy using ground-penetrating radar and estimating depths of argillic, spodic, and placic horizon or bedrock. These studies showed mean measurement errors between 2 and 40% (Doolittle and Butnor, 2009). The (topsoil)mineral soil/C horizon boundary or soil/bedrock boundary are the most often detected by ground-penetrating radar (e.g., Zhang et al. 2014; Ikazaki et al. 2018; Šamonil et al. 2020; Schaller et al. 2020; Schiavo et al. 2020), but there are only a few studies focusing on the depth of forest floor or topsoil (Li et al., 2015; Winkelbauer et al., 2011). These studies use conventional ground-penetrating radar surveying with subsequent processing of signal reflections to filtered 2D radargrams and interpret these. However, interpretation could be, to some extent, subjective. Winkelbauer et al. (2011) considered the first signal reflection as the surface and the following significant signal reflection as the lower boundary of the uppermost horizon. However, they could not distinguish individual organic horizons. The following reflection after the first reflection corresponded to topsoil/mineral soil or topsoil/bedrock boundary (Winkelbauer et al., 2011). We considered the same signal reflections as Winkelbauer et al. (2011), but we intended to interpret the ground-penetrating radar outputs more objectively. Thus, we compared the reflection amplitudes numerically trace by trace (publication IV). Nevertheless, the boundary between forest floor and topsoil was not detected. The first detected boundary corresponded to the topsoil/mineral soil boundary. Winkelbauer et al. (2011) argued that this failure resulted from insufficient thicknesses of the respective organic horizons relative to antenna resolution, as well as insignificant differences in dielectric permittivity. However, during our measurements, dielectric permittivity differences between forest floor and topsoil were more significant than that between topsoil and mineral soil in some cases. Insufficient topsoil thickness in Dystric Cambisol and that of the forest floor in Arenic Podzol could be the main reason why the boundaries were not detected. The topsoil/mineral soil boundaries were detected, although dielectric permittivities differed less than between forest floor and topsoil. Corradini et al. (2020) were also able to detect a boundary between layers showing a minimal dielectric permittivity difference, but they noticed that the peak of the reflection was weak. We could not distinguish the boundaries with low dielectric permittivity differences in the 2D radargrams because reflection was too weak; however, we distinguished these boundaries using numerical analysis of individual traces in one-dimensional analysis (publication IV).

By applying one-dimensional analysis, the thickness of the forest floor plus the topsoil was estimated with a 25 - 35% mean measurement error at the Cambisol site and 16 - 24% mean measurement error at the Podzol site (publication IV). The best comparable study by Winkelbauer et al. (2011) presents forest floor plus topsoil thickness estimation with a mean measurement error of 15%. However, they excluded sites with bigger stones or tree roots from the analysis (Winkelbauer et al., 2011). Tree roots and stones produce additional signal reflections and make interpretation difficult, as found at the Cambisol study site (publication IV). The tree roots are usually parts of organic horizons, so they should be filtered out during ground-penetrating radar data processing to not disturb the horizon boundaries. On the other hand, bigger stones often make the topsoil/mineral soil boundary. However, we were not able to distinguish between stones and tree roots at this stage, and it remains a challenge for future research. A way to distinguish stones and roots could be via the reflection coefficient (al Hagrey and Müller, 2000; Reppert et al., 2000). This method determines dielectric permittivity of an object from the magnitude of its reflection amplitude, while the permittivity of the medium (in this case, soil) must be known (al Hagrey and Müller, 2000; Reppert et al., 2000). Contemporaneously, this approach is used to determine soil water content where soil surface acts as an object and air as a medium (al Hagrey and Müller, 2000; Ardekani, 2013; Huisman et al., 2003). Dielectric permittivity of roots is between 4.5 for dry roots and 22 for water-saturated roots (al Hagrey, 2007), while dielectric permittivity of stones is between 3 and 5 (Cassidy, 2009). The dielectric permittivity contrast could allow their distinction.

Part of the measurement errors of forest floor and topsoil thicknesses mentioned above could be attributed to the ground-penetrating radar signal spreading from the device. The signal spreads like a cone, and it can cause a slight shift of irregular boundaries from the actual position (Fig. 4a). Another source of measurement error could originate from verification data collection. Ground-penetrating radar did not pass right over the documented profile but alongside to keep the survey transect undisturbed for following surveys. However, mean horizon thickness, used to calculate the organic mass, eliminates inaccurate object positions. This approach yielded estimation errors up to 9% for the Cambisol and up to 8% for the Podzol site. Thus, we suggest this method to facilitate the estimation of soil organic carbon pool.

We assume that irregular horizon boundaries could also be detected more precisely using 3D models, similarly to surveys of cryogenic wedges (Doolittle and Nelson, 2009; Watanabe et al., 2013); however, data collection for the 3D model is much more demanding (Bristow and Jol, 2003). Therefore, we do not consider the 3D approach effective for soil organic carbon estimation because the potential accuracy improvement would not pay for the time spent on additional fieldwork.

6.3. Effect of soil moisture conditions on estimation of forest floor and topsoil thicknesses

The surveys in publication IV were performed under several assumed soil moisture conditions at each site. However, moisture finally differed less significantly than expected based on weather conditions, probably because the subsoil drained much slower than topsoil at the Cambisol site and because the texture of individual horizons did not show any significant difference at the Podzol site (publication IV). For this reason, dielectric permittivity between the horizons differed only moderately (publication IV). Moisture conditions at field capacity (suggested advantageous by van Dam et al. (2002)) were almost met at the Cambisol site, but estimation error of point values was only slightly lower. Other studies (Curioni et al., 2017; van Dam et al., 2002; Zhang et al., 2014) show better results under wetter conditions. In contrast, we could see better deeper parts of irregular horizon boundaries under drier conditions because of limited signal attenuation. For this reason, surveying during dry conditions was suggested by Li et al. (2015). The mean thickness estimation error was the lowest under the driest conditions as well (publication IV). It follows that both wet and dry conditions can have advantages, depending on the survey objective. The same conclusion was drawn by van Dam et al. (2002).

6.4. Implications for soil organic carbon calculations

The accuracy of soil organic carbon stock estimation depends not only on the accuracy of thickness estimation using the presented ground-penetrating radar approach, but also on the accuracy of data on organic carbon concentration and bulk density. The laboratory methods used to determine both are well established, but uncertainty arises from spatial variability of these parameters in the field. Similarly, soil horizon thickness is highly spatially variable, as found and discussed in publication II. Therefore, thickness uncertainty arises not only from thickness estimation using ground-penetrating radar, but also from the ability to cover its spatial variability.

Tab. 5 Organic carbon concentration in forest floor of soils in studied catchments

locality	min	max	average	range	standard deviation	
	%	%	%	%	%	% of average
ANE	39.4	44.4	41.9	5.0	1.78	4.2%
CER	33.1	45.4	38.2	12.4	4.29	11.2%
JEZ	25.0	40.7	36.0	15.7	4.12	11.4%
LES	28.7	46.0	39.0	17.3	5.13	13.1%
LIZ	38.1	46.7	42.8	8.7	2.94	6.9%
LKV	41.8	45.7	43.5	3.9	1.55	3.6%
LYS	32.4	42.6	39.2	10.3	4.11	10.5%
MOD	30.6	45.2	40.1	14.7	4.36	10.9%
PLB	40.9	42.2	41.5	1.3	0.44	1.1%
POM	33.9	43.7	39.4	9.8	3.91	9.9%
SAL	39.7	46.7	45.0	7.0	2.07	4.6%
UDL	39.0	42.0	40.7	3.1	1.22	3.0%
UHL	34.7	42.2	37.6	7.6	2.36	6.3%
NAZ	34.5	42.2	38.7	7.7	2.73	7.1%
all data	25	46.7	40.0	21.7	4.29	10.7%
average per catchments	35.1	44.0	40.3	8.9	2.93	7.4%

Source: data from forested catchments (Fig. 7, publication I)

Among the three soil properties needed for soil organic carbon stock estimation, carbon concentration seems to show the least spatial variability (Tab. 5). Organic carbon concentration in the forest floor reaches 25-47% over all studied soil profiles across catchments (publication I, Fig. 7), with a range of 22% and standard deviation of 4%, representing 11% of average value. However, variability within individual catchments with an area of a few kilometres is lower. The average range of carbon concentration within a catchment is 9%, with a standard deviation of 7% of average carbon concentration (Tab. 5). Still, published carbon concentration in topsoil at a locality with similar soils shows comparable values. Soil organic carbon concentration reached 15-24%, with a standard deviation of 18% of average value (Valtera and Šamonil, 2018).

Tab. 6 Bulk density of forest floor of soils in studied catchments

locality	min	max	average	range	standard deviation	
	g/cm^3	g/cm^3	g/cm^3	g/cm^3	g/cm^3	% of average
ANE	0.05	0.19	0.14	0.14	0.05	35.7%
CER	0.08	0.18	0.13	0.10	0.03	26.6%
JEZ	0.04	0.42	0.17	0.38	0.09	55.7%
LES	0.04	0.19	0.11	0.15	0.06	51.4%
LIZ	0.05	0.17	0.10	0.12	0.05	45.3%
LKV	0.06	0.11	0.09	0.05	0.02	20.1%
LYS	0.07	0.18	0.12	0.10	0.04	32.2%
MOD	0.05	0.17	0.11	0.12	0.04	38.1%
PLB	0.12	0.23	0.16	0.11	0.05	28.5%
POM	0.08	0.21	0.14	0.12	0.04	29.3%
SAL	0.07	0.16	0.13	0.09	0.03	21.9%
UDL	0.09	0.17	0.13	0.08	0.03	24.7%
UHL	0.08	0.21	0.15	0.13	0.04	26.1%
ZEL	0.06	0.17	0.12	0.11	0.04	33.6%
all data	0.04	0.42	0.13	0.38	0.05	42.5%
average per catchment	0.07	0.20	0.13	0.13	0.04	33.5%

Source: data from forested catchments (Fig. 7, publication I)

Forest floor soil bulk density shows higher variability (Tab. 6). It reaches 0.04-0.42 g/cm^3, with a range of 0.38 g/cm^3 and standard deviation of 42.5% of average value across all catchments. However, similar to carbon concentration, variability is lower within individual catchments showing a range of 0.13 g/cm^3, with standard deviation of 33.5% of the average value. Topsoil soil bulk density at a comparable locality with similar soils studied by Valtera and Šamonil (2018) reaches 0.35-0.48 g/cm^3, with a standard deviation of 12% of average value.

High variability was also reported for forest floor thickness (Tab. 7). Thickness values are between 1-15 cm, with a 14 cm range and a standard deviation of 44% of average value. This variability is higher between catchments than within individual catchments. The average range per catchment is 6.6 cm, and the standard deviation is 34% of average value (Tab. 7).

Tab. 7 Forest floor thickness of soils in studied catchments

locality	min	max	average	range	standard deviation	
	cm	cm	cm	cm	cm	% of average
ANE	1.3	5.7	3.9	4.4	1.5	37.2%
CER	5.3	12.3	7.5	7.0	1.9	26.0%
JEZ	3.0	11.5	7.4	8.5	2.7	36.7%
LES	3.5	9.3	5.4	5.8	1.7	31.6%
LIZ	3.0	11.7	5.9	8.7	3.0	50.3%
LKV	1.8	7.8	4.3	6.0	1.8	42.4%
LYS	3.7	14.9	8.3	11.2	4.2	50.3%
MOD	2.8	13.3	8.5	10.5	3.5	41.2%
PLB	3.9	11.2	6.7	7.3	2.7	40.8%
POM	4.0	8.0	5.9	4.0	1.3	22.5%
SAL	3.7	9.1	5.8	5.4	1.5	26.2%
UDL	6.7	9.2	8.0	2.5	0.8	10.6%
UHL	9.0	13.8	10.6	4.8	1.6	14.9%
ZEL	1.8	7.7	4.3	5.9	1.9	43.8%
all data	1.3	14.9	6.7	13.6	2.9	43.8%
average per catchments	3.8	10.4	6.6	6.6	2.2	33.9%

Source: data from forested catchments (Fig. 7, publication I)

High variability of measured variables inevitably influences the uncertainty of soil organic carbon stock estimation because uncertainties of all variables propagate. Hypothetical uncertainty (most pessimistic scenario) of estimation of soil organic carbon stock in the forest floor plus topsoil at one of the catchments, where all the necessary data were collected (Liz catchment,) would be as follows (Taylor, 1982): $U = (\sigma_c^2 + \mu_c^2)(\sigma_{BD}^2 + \mu_{BD}^2)(\sigma_T^2 + \mu_T^2)(\sigma_{GPR}^2 + \mu_{GPR}^2) - \mu_c^2 * \mu_{BD}^2 * \mu_T^2 * \mu_{GPR}^2$; where U is uncertainty expressed as the variance of the estimation; $\boldsymbol{\sigma}$ is standard deviation; μ is mean value; lowercase indices next to mean and standard deviation symbols stand for: *c* - organic carbon concentration, *BD* - bulk density, *T* - thickness, *GPR* - thickness error originated in using ground-penetrating radar. The uncertainty of estimating soil organic carbon stock in the forest floor plus topsoil using thickness measured by ground-penetrating radar exceeded 80% if expressed as standard deviation in the value relative to average thickness. However, uncertainty of stock estimation using thickness measured manually in the field at more than 164 random sampling pits per 1 km^2 (publication II) reached almost 60%. It follows that the major uncertainty originates in spatial variability of soil properties. In absolute values, the organic carbon stock in the forest floor plus topsoil at the Liz catchment was estimated to be 61.5 t/ha using thickness from sampling pits. In comparison, estimation based on thickness acquired by ground-penetrating radar was 57 t/ha. The difference between these two approaches is less than 8%. In addition, if thickness measured manually along the ground-penetrating radar transect (point values) for the method verification is used instead of thickness from sampling pits, the difference to ground-penetrating radar estimation is under 5%. It follows that the uncertainty originates from the spatial variability of the used parameters.

Uncertainty originating from thickness spatial variability could be reduced by a higher density of ground-penetrating radar transects. However, this approach could potentially meet problems with reduced output clarity and higher signal attenuation in lower layers caused by dense understory vegetation and forest litter, especially leaf litter (Tanikawa et al., 2016) or attenuation caused by higher clay content in mineral soil (publication III). Some authors state that in soils with 35% clay contents and above, penetration depth of ground-penetrating radar measurements using frequencies over 500 MHz (commonly used for soil surveys) might not reach more than 0.5 m (Doolittle and Butnor, 2009). However, the depth of 0.5 m usually suffices for surveys of forest floor and topsoil. Signal attenuation due to dense understory vegetation was not observed in the studied transect as the transect line was mainly covered by needles, with some patches of moss and sparse grass.

7. Conclusions

Forest floor carbon pool represents only 25% of the total soil organic carbon pool down to a depth of 80 cm, and it is the least recalcitrant part that is subject to the most rapid changes. Therefore, its estimation is essential for monitoring soil organic carbon pool changes. Forest floor and topsoil thicknesses are highly variable; thus, the soil organic carbon pool is variable accordingly. Several factors controlling this variability were identified at the regional and local scale: elevation; soil moisture; historical soil acidification; tree species; forest floor cover; and soil texture. Although processes acting at both scales are similar, the best predictors differ slightly. We found that elevation can be used as a variable representing climate for soil organic carbon modelling in regional studies in Central Europe. Still, in local studies, it is better to use soil moisture that shows the microclimate of a site. At the regional scale, vegetation expressed as a proportion of broadleaf trees and conifers was a significant predictor of the soil organic carbon pool. In contrast, at the local scale, forest floor cover (needles, leaves, graminoids, moss, bilberries, spruce seedlings) predicted the soil organic carbon pool better.

The driving factors of soil organic carbon pool also change with depth. The climate controls the total soil organic pool, but its effect on the forest floor carbon pool is outbalanced by the effect of organic matter deposition, its recalcitrance, and by acid deposition retarding mineralization. Ground-penetrating radar can help estimate forest floor and topsoil thickness, and thus model their organic carbon pool. However, conventionally processed ground-penetrating radar outputs are often subjective. We proposed a more objective approach, treating reflection amplitudes trace by trace. This method still does not reveal the forest floor and topsoil boundary. The topsoil/mineral soil boundary was detected with a mean measurement error of 25%. However, when using mean thicknesses for a several metres long transect, the measurement error is only up to 9%. Better results at points were obtained under wetter conditions, but not significantly. By contrast, under drier conditions, deeper parts of irregular horizon boundaries could be better detected and mean thickness was more accurate. This approach could be improved by distinguishing tree roots and stones, which remains a challenge for future research.

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9. Supplements

9.1. Publication I

Chuman, T., Oulehle, F., Zajícová, K., Hruška, J., 2021. The legacy of acidic deposition controls soil organic carbon pools in temperate forests across the Czech Republic. European Journal of Soil Science 72, 1780–1801. https://doi.org/10.1111/ejss.13073

9.2. Publication II

Zajícová, K., Chuman, T., 2021. Spatial variability of forest floor and topsoil thicknesses and their relation to topography and forest stand characteristics in managed forests of Norway spruce and European beech. European Journal of Forest Research 140, 77–90. https://doi.org/10.1007/s10342-020-01316-1

9.3. Publication III

Zajícová, K., Chuman, T., 2019. Application of ground penetrating radar methods in soil studies: A review. Geoderma 343, 116–129. https://doi.org/10.1016/j.geoderma.2019.02.024

9.4. Publication IV

Zajícová, K., Chuman, T. (in review). O and A soil horizons' boundaries detection using GPR under variable soil moisture conditions. Geoderma