

1 **Measuring and monitoring soil carbon sequestration**

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5 *Key words: MRV; SOC sequestration; soil measurements; SOC modelling*

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7 1 Introduction

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17 Abstract

18 The monitoring, reporting and verification (MRV) of soil organic carbon (SOC)
19 sequestration following management changes is complex due to the multitude of
20 influencing factors related to ecosystem processes but also due to (socio-)economic
21 or legal requirements. Several protocols for MRV applications have been published.
22 In this chapter we will provide an overview about available systems and their
23 advantages and limitations. There is a wide range of options to quantify SOC changes,
24 but most of these options have limitations. Field measurements, including periodic on
25 site measurements, short-term experiments and long-term monitoring are time
26 consuming, cost and labour intensive. On the other hand modelling, and/or remote
27 sensing approaches are associated with uncertainty, and/or data demand. Therefore,

28 an effective MRV application should be a combination of different approaches. This
29 chapter will discuss the different aspects, which will be picked up in the other chapters
30 of this section that will present more details on quantification options.

31

32 *1 Introduction*

33 Soils have recently received attention in the context of climate change, because they
34 are the largest terrestrial carbon pool (Batjes, 1996, Lal, 2004) and small changes of
35 this large reservoir may affect atmospheric CO₂ concentrations. To preserve current
36 atmospheric CO₂ levels and to limit climate change impacts it is thus important to
37 protect the carbon stored in soils and prevent its release to the atmosphere. Carbon
38 may be stored in soils at long timescales and soil carbon sequestration may therefore
39 have a large potential as negative emission technology (Paustian et al., 2016, Minasny
40 et al., 2017, Paustian et al., 2019). Such technologies need to be employed to meet
41 the climate targets of the Paris Agreement or the different national net zero targets
42 (Climate Ambition Alliance: Net Zero 2050). Increasing soil organic carbon (SOC)
43 sequestration will remove atmospheric carbon and store it in the soil. This process can
44 have a range of positive side effects (Smith, Pete et al., 2021). Rumpel et al. (2018)
45 describes eight steps to make soil more resilient, more productive and improve the
46 storage of carbon. One central part for awarding land managers for improving soils
47 and for the application of SOC storage as a large-scale climate mitigation strategy, is
48 the availability of a system for measuring, reporting and verification (MRV) of the effect
49 of land management practice. This includes the quantification of SOC changes over
50 time. However, SOC sequestration is a complex and slow process affected by a wide
51 range of factors (see Chapters 3, 4, 5). This makes the measurement and monitoring
52 of SOC challenging. While point measurements are associated with errors and
53 uncertainties, large-scale quantification presents even more challenges, as it requires
54 either large amounts of samples, which is costly and labour intensive, or upscaling
55 methods based on assumptions.

56 Soils are used for different purposes and often managed by a variety of users with
57 their own interests. Activities to increase SOC are not necessarily the main interest of
58 the users and/or landowners. Farmers, for example need to rely on constant harvest
59 to provide food and make a living. Incentives or legal obligations are required to

60 introduce changes to maintain and/or increase SOC (see Chapters 26, 27 and 29),
61 and their implementation depends on a functional monitoring system. This system will
62 be based on available and future development of tools and approaches to quantify
63 SOC changes (measurements, modelling, etc.). Available tools show a wide range of
64 complexity and accuracy, with a general trend towards application of simpler options
65 with easy, cheap and rapid methods.

66 To account for varying complexity of methodologies, the IPCC introduced a three-step
67 tier-system, with Tier 1 indicating a basic method with an equation and default
68 emission factors, Tier 2 using the same equation but country / region-specific emission
69 factors and Tier 3 any more complex method, ranging from alternative equations to
70 process-based models.. The equation and default factor for Tier 1 describe a linear
71 relation between an activity (e.g. fertilizer application on the field) and the related
72 estimated GHG emissions. Scientific data build the basis for this relation, which is a
73 simplified, but effective and standardised approach to estimate GHG emissions. While
74 the used values in Tier 1 are more generic (based on global data), the Tier 2 approach
75 is similar to Tier 1, but uses country specific values that provide a more accurate
76 estimate for the target country. Available emission factors are summarised in the
77 emission factor database (EFDB; <https://www.ipcc-nggip.iges.or.jp/EFDB/main.php>).

78 There is an increasing interest in the economics of carbon sequestration. While there
79 is already an interest in an investment in more sustainable companies (Kareiva et al.,
80 2015), carbon accounting and trading of carbon units generated by SOC sequestration
81 has started already. However, all of these different interests rely on a functional and
82 applicable MRV system. Recent research focussed focused on MRV applications and
83 has developed suitable frameworks (Paustian et al., 2019, Smith et al., 2020, FAO,
84 2020). In this chapter we will present available systems and discuss their advantages
85 and limitations

86

87 *2 Measurement/monitoring, reporting and verification (MRV)*

88 In this chapter we distinguish MRV frameworks from MRV applications. While a
89 framework provides a more theoretical description of an optimum MRV system, the
90 application describes an applied MRV system, using protocols that include concrete
91 definitions of used models, measurement approaches and other required details (e.g.

responsibilities for the different actions). Smith *et al.* (2020) outlined a generic concept for an MRV framework as a combination of different approaches to quantify SOC change over time. Generally, management changes are applied on a field or farm level. The farm level is the scale for the beneficiaries of subsidies or carbon trading. Therefore, field and farm scale are most relevant to an MRV scheme. A central part of quantifying SOC changes on this scale are field measurements, but these are costly and labour intensive. Additionally, MRV protocols often lack clear measurement standards (Bispo *et al.*, 2017). While some aspects are clarified (depth of the top 30 cm, 1 m if possible (FAO, 2020)), other specifications are missing (number of samples, date of sampling relative to the management practices, spatial distribution of sampling, etc.). Therefore, alternative approaches to measurements need to be considered. Modelling is a very attractive alternative, as all problems and limitations of the measurements are resolved by using a model. But the quality of the simulation result needs to be considered, especially in comparison to measurements. Models include errors and uncertainty based on the assumptions used and the underlying concepts and they require data for calibration and validation, in addition to those needed for running the models. MRV frameworks as outlined by the FAO (2020) and Smith *et al.* (2020) specify that only calibrated models can contribute to SOC quantification, but further specification of the models is not provided. A combination of both (measurement and modelling) will compensate the disadvantages of each other and improve the result (Smith *et al.*, 2020). Overall, a combination of different approaches secures the optimum quantification of SOC changes over time. Smith *et al.* (2020) list seven components of an MRV framework: long-term experimental sites, field experiments (short-term), field specific modelling, spatial data analysis combined with modelling, collection and aggregation of activity data (e.g. conventional and intervention management), remote sensing and spatial re-sampling. The different components complement each other to allow an optimum framework for measuring and verifying SOC changes over time. There are advantages and disadvantages of all different components and all show some limitations. Only a combination of all, or at least several of these methods, will provide good MRV outcomes.

122

123 2.1 Measurements

124 Direct measurements of SOC content involves quantifying the fine earth and coarse
125 earth fraction, the organic carbon concentration and soil bulk density or fine earth
126 mass (FAO, 2019). Estimating the rock content of sample soils can be a challenge but
127 will significantly affect soil bulk density (Poeplau et al., 2017, Throop et al., 2012).
128 Another challenge is that a change in management (whole practice as well as depth
129 at which that practice is applied), will not only impact on the bulk density of the soil but
130 also on the amount of soil in a soil sample at a certain depth (Haynes, 1998).
131 Therefore, corrections and use of the equivalent mass approach may be necessary
132 (Chapter 11). As soils are characterised by a high spatial variability, direct
133 measurements rely on appropriate study designs and sampling protocols (Minasny et
134 al., 2017, Chapter 11). At the field scale, large number of soil samples is usually
135 required to give reliable SOC stock estimates with an acceptable error margin (Garten
136 & Wullschleger, 1999, Vanguelova et al., 2016).

137 IPCC recommends a sample depth of 30 cm, but several methods for increasing SOC
138 content require deeper sampling for confirming the expected effect (Smith et al. 2020).
139 For example, the effect of a no tillage practice on the SOC content may be
140 overestimated if the measuring depth is insufficient (Angers & Eriksen-Hamel, 2008,
141 Blanco-Canqui, Lal, 2008).

142 A change in SOC stocks can also be estimated through indirect measurements and
143 by presenting the full carbon budget. This approach uses the net balance of carbon
144 fluxes measured through chamber measurements or the eddy covariance (EC)
145 method (Baldocchi, 2003). From the carbon fluxes, the initial uptake of carbon through
146 photosynthesis and its subsequent partial loss through respiration (from soil, plant and
147 litter) are estimated to give net ecosystem exchange or net ecosystem production and
148 further C inputs (organic fertilization) and outputs (harvest) to and from the system
149 (Smith et al., 2010, Soussana et al., , 2010). Through this compiled carbon budget, a
150 change in SOC can be estimated. This approach indirectly measures the change in
151 SOC for larger landscapes but can only be used under horizontal homogeneity of the
152 footprint area and under sufficient air turbulences (Aubinet et al., 1999). The
153 maintenance of most measurement systems is costly and time consuming. The post
154 processing of the measured data is also needs time and expert knowledge about flux
155 corrections for density and gap filling (Falge et al., 2001, Reichstein et al., 2005). In

156 an MRV application EC provides landscape specific data, which can be used as
157 baseline data or for model optimisation purposes (calibration and validation).

158

159 Long-term study sites are crucial for the implementation of MRV framework (Smith et
160 al., 2020). Study sites for different management combinations allow a long-term
161 observation and quantification of all relevant parameters and variables that affect the
162 SOC sequestration. 'Long-term' is relative and not defined as a fixed duration. The
163 IPCC suggests 20 years as the default period to observe SOC changes, because SOC
164 sequestration rates are fast at the beginning, but slow down over time until they
165 approach zero (Sommer & Bossio, 2014). Measurements are impractical for a generic
166 implementation of an MRV process (too costly and labour intensive) and other
167 solutions that replace or at least reduce the sampling intensity in the field are required.
168 Besides modelling and remote sensing, long-term study sites in combination with
169 short-term field experiments can complement field measurements. These study sites
170 provide data for re-assessment of potential impacts, reference for expected changes
171 or baseline for a particular management practice. Additionally, these data will be the
172 basis for development, calibration and validation of models and remote sensing
173 approaches. Ideally, land cover, soil, climate, management and environmental
174 conditions are represented by available study sites or at least a reasonable number of
175 combinations (good representation of all climate zones, soil types, crop species, etc.).
176 A standard protocol for the acquisition of these data would be beneficial, because
177 differences in the set-up of the measurement approaches could introduce uncertainty.
178 Organizing and providing these data on accessible platforms is the best way for an
179 open and transparent handling of the data. Two platforms for long-term experimental
180 sites were initiated by the SOMNET (Smith et al., 2002) and the EuroSOMNET
181 (<https://www.ufz.de/somnet/>),(Franko et al., 2002)) platforms. The SOMNET platform
182 evolved later to an online, real-time inventory project including a webpage with Long -
183 Term Soil - Ecosystems Experiments. The database contains meta-data of more than
184 200 long-term experiments and is hosted by the International Soil Carbon Network
185 (<http://iscn.fluxdata.org/network/partner-networks/ltse/>). More than 80 % of the long-
186 term experimental sites concern agricultural systems (Smith et al., 2012). However,
187 the majority of the sites are in the temperate climate zone with focus on Europe and
188 North America, under-representing tropical and sub-tropical regions and the Southern

189 hemisphere (Smith et al., 2012). For good coverage of the variability of global
190 agricultural systems, more long-term sites in other parts of the world need to be
191 established. The better the representation of different management options, soil and
192 climate zones by experimental sites, the better the data basis for MRV application.
193 This requires immediate action, as study sites that are established today, will be able
194 to be used to assess long-term effects on SOC in 20 years (Smith et al., 2012). Special
195 funding is required to initiate long-term monitoring sites, as project funding for 3 to 5
196 years duration is insufficient.

197

198 *2.2 Remote sensing*

199 Beside *in-situ* measurements, remote sensing can support the monitoring of SOC
200 changes and/or provide data for the verification of measured SOC changes. This
201 technology allows non-invasive measurements, including at large scale. Remote
202 sensing can be applied in the lab or on the field by handheld or transportable systems,
203 or by airborne or satellite device devices (Chabrilat et al., 2019). As part of an MRV
204 application the latter two options are more useful, as these systems allow a wider
205 coverage and delivery of large-scale data globally. Considering the wide application
206 and availability of the data, this would reduce costs for monitoring SOC changes
207 (Nocita et al., 2015), once the approach is established. There are different approaches
208 used for SOC estimation and two of them are highlighted below.

209

210 One established remote sensing approach is the reflectance spectroscopy. It uses
211 characteristic spectra that are reflected from the soil surface for quantitative and
212 quantitative analysis of soil properties. The recommended wavelength range for these
213 measurements is the visible near infrared–shortwave infrared (700-2500nm), as it
214 shows a good signal to noise ratio and is a cost and time effective option for
215 spectroscopy (Mohamed et al., 2018). The characteristic spectra are reflected by the
216 bonds in the SOC molecules (O-H, N-H, C-H), which allow a qualitative and
217 quantitative analysis of SOC. This method provides soil-type-specific quantitative SOC
218 estimates (Grinand et al., 2012). To secure a wider application without site specific
219 measurements, spectral libraries are required that contain several thousand soil types
220 with varying soil properties, as a reference. This is a cost- and time-effective

221 alternative to other traditional measurement options in the laboratory, such as wet
222 digestion or dry combustion (Nayak et al., 2019).

223

224 The introduced high spectroscopy measures for fixed wavelength using multispectral
225 sensors, which is associated with some limitations, especially for quantitative
226 measurements on SOC (Ben-Dor et al., 2018). Therefore, recent developments on
227 hyperspectral sensors show an improved approach with higher capability for
228 quantitative data over large areas. Hyperspectral remote sensing (also called image
229 spectroscopy) provides a continuous spectrum for each pixel, using 100 or more
230 contiguous spectral bands. However, Ben-Dor et al. (2018) also list a wide range of
231 drawbacks with the signal to noise ratio as a major problem (caused e.g. by non-
232 transparent atmosphere, problems with sensor calibration) and more problems with
233 changing conditions (e.g. changes in soil particle size). Further developments are
234 required to improve the approach. For large scale application, there is again a demand
235 for developing new libraries for the new approach.

236

237 The advantage of large scale remote sensing using airborne devices and/or satellites
238 is that it can provide additional information, e.g. land use change (Winkler et al., 2021),
239 primary production (Zhao et al., 2005) or different soil properties (Viscarra Rossel et
240 al., 2006). Nevertheless, remote sensing has limitations. The availability of images is
241 affected by cloud cover, measurements are affected by plant cover on the ground and
242 only the top centimetre can be measured (Smith et al., 2020). Despite good results in
243 different studies and the availability of spectral libraries, the measurement is still
244 uncertain, which renders remote sensing as the sole MRV method unsuitable. In
245 contrast, it is an excellent additional approach to complement other methods, and
246 should therefore be used only in combination.

247

248 The latest developments in multi-spectral systems to quantify SOC have shown great
249 progress (Aldana-Jague et al., 2016). These kind of measurements have the potential
250 to reduce uncertainty (Chabrilat et al., 2019), new libraries have to be built for the new
251 approach. Chabrilat et al. (2019) refers also to studies using hyperspectral systems
252 (Gomez et al., 2008, Lu et al., 2013), but rates the performance as moderate. Similar
253 to the other approaches, remote sensing shows a good potential to complement

254 measurements and reduced costs but is not able to replace field measurements
 255 completely.

256

257 *2.3 Modelling*

258 As there are limitations to field measurements and remote sensing,,modelling
 259 becomes the most prominent supplement to provide data for MRV application. Models
 260 can contribute in different ways to MRV: 1) provide baseline information, 2) interpolate
 261 measurements (temporally and spatially), 3) extrapolate measurements for projections
 262 or for an ex-ante assessment, 4) estimate SOC changes, and 5) provide information
 263 for an optimised measurement plan. Different models with different complexity and
 264 accuracy can be used in MRV application. However, there are no standards defining
 265 the quality of a model used in an MRV application. Choosing the right model depends
 266 on the objective, data availability and modelling skills of the user (Table 1), as different
 267 models vary in their characteristics, complexity and accuracy (Table 1).

268

269 Table 1: Specifications for different model categories. The category emission factors
 270 also include simple empirical equations (Tier 2 approaches). The categories SOC and
 271 biogeochemical models (Tier 3 approaches) are separated to indicate if a model only
 272 includes SOC dynamics or also addresses processes (e.g. N cycle, plant growth). The
 273 category decision support includes tools that are designed to provide information on
 274 GHG emissions, SOC changes or both (these tools use mainly Tier 1 and Tier 2
 275 approaches but can also include Tier 3 routines).

	Emission factors	Decision support tools	SOC models	Biogeochemical models (Tier 3)
Data requirement	low	high (farm specific data)	high (environmental data)	high (environmental data)
Calibration requirement	low	low	high	high
Required expertise	low	medium	high	high

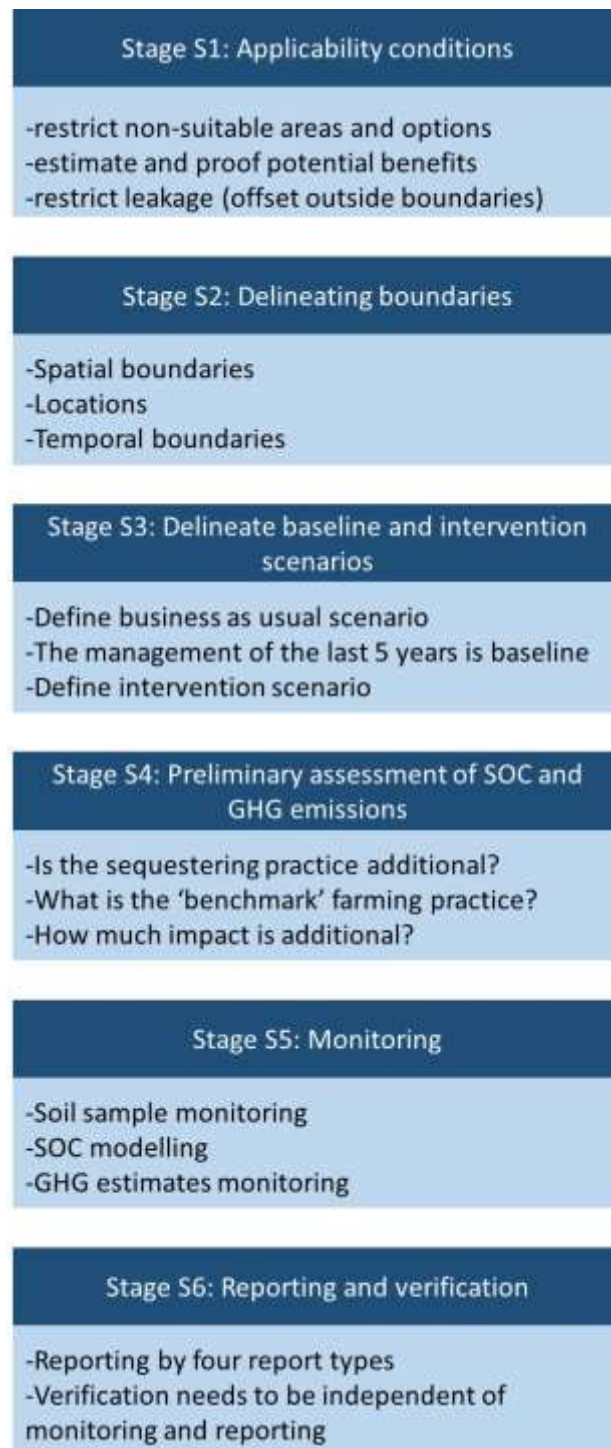
Management options	medium (categories)	medium- high	no-high	high
Targeted scale	country and larger	field -farm	point/site	point/site
Uncertainty/expected error for field scale	high	medium- high	low	low
Example models	UNFCCC models, Tier 1, Tier 2	Cool Farm Tool, Comet Farm Tool	RothC	EPIC, DAYCENT, DNDC

276

277 Biogeochemical models seem to be most suitable for MRV approaches, as they are
278 able to simulate SOC with the highest accuracy and provide additionally information
279 about impacts on yield and GHG emissions (Camino-Serrano et al., 2018, Campbell
280 and Paustian, 2015). However, these models are sometimes impractical, as they
281 require a large amount of data and expert knowledge to use them. Emission factors
282 and simple equations are often used by carbon trading platforms, but these models
283 are developed for large scale (country scale) application and might show large errors
284 on the field scale. Most suitable seems to be decision support tools for carbon
285 accounting, like the Cool Farm Tool (<https://coolfarmtool.org/>, (Hillier et al., 2011)) or
286 COMET-Farm (<http://comet-farm.com/>, (Paustian et al., 2017)), as they address or
287 show the potential to address the aforementioned problems of the emission factors
288 and process based models (Whittaker et al., 2013). These tools use different routines
289 of different complexities (Tier 1 to Tier 3, depending on the tool). Unfortunately, the
290 most popular options also show limitations, as the SOC component of the Cool Farm
291 Tool (CFT) uses the Tier 1 approach of the IPCC 2006 guidelines (although this is
292 under review in the moment) and the COMET-Farm Tool uses a Tier 3 approach in
293 combination with a data base that only covers the USA. Further developments of both
294 tools are ongoing, and in the future, these may be reasonable options. Both tools are
295 developed for stakeholders with an easy-to-use interface. The CFT was developed
296 with an interface usable by farmers and the input information they have at hand. The
297 CFT calculates the GHG emissions on a farm level for a specific site and specific
298 management. The methods used within CFT range from emission factors to a model

299 approach considering region specific parameters and farm level data (e.g.
300 management, soil, climate) on an annual basis. Therefore, the CFT can be seen as a
301 Tier2 or simple Tier 3 model. COMET-Farm calculates the carbon footprint of a farm.
302 The tool provides the opportunity to test different management interventions and
303 explore their mitigation potential, i.e. the potential reduction of GHG emissions. GHG
304 estimates for crops are calculated using the DayCent dynamic model (Del Grosso et
305 al., 2010, Parton et al., 1998)– a process-based model - and follows the official USDA
306 GHG inventory guidelines for entity-scale reporting (Eve et al., 2014). Both tools
307 consider soil carbon sequestration and calculate the SOC change for a land use
308 change or change in soil management.

309



310

311 Figure 1: The MRV framework of (FAO, 2020) follows a 6-stage approach to set up a
 312 MRV protocol.

313

314 *3 Existing MRV protocols*

315 FAO (2020) published a protocol that provides concrete guidelines about the structure
 316 and steps to apply an MRV application (Figure 1). The FAO protocol differentiates

317 reporting into four different categories: 1) pre-implementation report, 2) initial report,
318 3) biannual report and 4) final report. These reports describe the different stages of
319 MRV frameworks as outlined in Figure 1. The protocol also provides suggestions and
320 guidelines for the responsibilities for MRV framework. It is suggested that the reporting
321 can be organised by the farmer but needs to be done in consultation with a relevant
322 expert. An independent person or entity must verify the reports. The monitoring and
323 verification require expert knowledge, which can be secured by accreditation of
324 independent experts specialised in these activities and by external expert reviews,
325 respectively. The accreditation and certification can be organised by governmental
326 institutions (e.g. for subsidies), other large organisations (e.g. FAO or entities). Certain
327 specifications are not included (e.g. measurements approaches, suitable models) as
328 the protocol is a blueprint for a global use and might require local adaptation.

329

330 In addition to FAO's standardised framework, two other examples of MRV protocols in
331 Alberta, Canada and Australia are already in place. The Government of Alberta
332 published an MRV protocol to quantify impacts of tillage management on GHG
333 emissions and SOC. It differs from the FAO protocol by specifying the target area and
334 the management to be applied, which allows some aspects to be considered in more
335 detail. For example, some reversal events are allowed for natural farms. Conventional
336 tillage is allowed in less than 10% of the farm area for weed control. Another protocol
337 has been published by the Australian Government (Australian Government., 2018),
338 which includes bare land and pastures alongside croplands for baseline conditions.
339 This protocol has a similar structure and content as the FAO framework, but it is more
340 specific on defining in some detail the management options that are allowed but differs
341 in some other details (e.g. review every 5 years).

342

343 Carbon accounting platforms have also started to trade carbon based on SOC gains.
344 The good standards of the protocols are undermined by their implementation. One
345 example for the actual protocols is the Verified Carbon Standard (Shoch, Swails et al.
346 2020). Measurements are very limited (one measurement suggested), SOC changes
347 are quantified by Tier 1 models and the project time is restricted to a short period (e.g.
348 10 years). The implementation of a simple MRV application by businesses is

349 economically motivated. Even though, there is a demand for cost reduction, the
350 methods applied need to be improved, to provide an adequate data for carbon trading.
351 Nevertheless, improvements in this sector would provide a business solution that will
352 improve mitigation actions once a functional system is established.

353

354 *4 Outlook of the use of MRV applications*

355 MRV applications are essential to the implementation of strategies to mitigate climate
356 change (Smith, Pete, Soussana et al. 2020). It is also a requirement for subsidies from
357 governmental institutions, carbon trading or for the initiatives of companies with net
358 zero targets (FAO 2020, Kareiva, McNally et al. 2015, Paustian, Collier et al. 2019). In
359 contrast to MRV applications for other processes or variables, monitoring of SOC stock
360 changes has additional challenges; (1) the slow rate of change in soil carbon against
361 the large background stock, (2) the heterogeneous distribution in space and depth, (3)
362 the complexity of measurements and the reversibility of the gains, which make the
363 requirements of MRV complex. MRV protocols overcome these problems by applying
364 a combination of different methods, to compensate for limitations of individual
365 quantification methods. The implementation of MRV applications require an integrated
366 approach but barriers exist. The combined approach can be costly, labour intensive
367 and/or requires a wider skill set (or even expert knowledge). In summary, current MRV
368 methods are often impractical for stakeholders.

369

370 In the near future, the challenge for science is to reduce complexity and to remove
371 these barriers in order to provide practical solutions. One relatively easy target could
372 be the development or improvement of models, that are easily applicable by
373 stakeholders, but that provide robust results at the field and farm scale. More
374 challenging and more time intensive will be the further development of remote sensing
375 approaches. Remote sensing will never be able to replace the field measurements,
376 but it will improve the quality of the measurements and might allow for a reduction of
377 the number of samples to save labour time and lower costs.

378

379 Other approaches like digital mapping will also contribute to an improved
380 understanding and to quantification of SOC changes. Such developments have the
381 potential to improve the measurements in MRV applications.

382 The following chapters will further detail some aspects of MRV approaches. Chapter
383 11 will give an overview on methods for quantifying SOC stocks and characterising its
384 turnover times at the profile scale. Chapter 12 will introduce the digital soil mapping as
385 an additional option to quantify SOC on a farm level (De Gruijter et al., 2015). The
386 chapter will indicate the advantages and limitations of this approach, including the
387 measurement demand and the associated uncertainty. Chapter 13 will give a detailed
388 overview on SOC modelling approaches with special focus on its permanency. Finally,
389 Chapter 14 will outline digital stock taking, with the focus on the field scale. This will
390 include an analysis of knowledge gaps in field-specific digital stock taking and new
391 approaches, such as application of smartphones to quantify SOC stocks. These
392 methods will be discussed in the context of an application in MRV applications, which
393 would bring down measurement costs and potentially improve accuracy.

394

395 *5 Summary*

396 Sequestering atmospheric carbon through increases SOC stocks requires a functional
397 MRV application to monitor impacts of management practices on the soil. A single
398 quantification approach is not sufficient; instead a combination of different methods is
399 necessary to monitor SOC changes over time and to provide appropriate verification
400 methods. For simplified MRV applications, there is a risk for errors and uncertainty.
401 Developments of the available tools do not all meet the demands for an MRV
402 applications applied for different purposes. There is an imbalance between complexity
403 and accuracy (for modelling) as well as in costs and accuracy (measurements). The
404 chapters in this section describe currently available approaches and future
405 developments that might provide effective solutions to be applied in MRV applications.
406 The approaches presented do not target the implementation in MRV applications, but
407 they are measurement tools, which can be used in MRV applications.

408

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411

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