Public Comment
CarbonPlus Methodology & Credit Class for GHG and Co-Benefits in Grazing Systems

December 6, 2023

REVIEWER	REVIEWER'S COMMENT	AUTHOR'S RESPONSE Please describe how the comment was addressed and include new content in quotations	Reviewer's Conclusion [PASSED/ REJECTED WITH COMMENTS]
Sam Duncan, MSc., CEO at Farmlabs	Really great new method, I don't have a lot to add, but perhaps some suggestions: Section 3.3.1.2.OptionA.CORRELATION BETWEEN SOC PERCENTAGE AND REMOTE SENSING DATA	-No action (N/A) required-	

Sam Duncan, MSc., CEO at Farmlabs	- Really liked the sampling density calculator. The results match up with some of the research we've done internally on the spatial distribution of carbon and the number of samples required to accurately measure it. We've used the elbow curve method in the past for some farms, and consistently come up with very similar figures to what your calculator provides (about 24-28 samples for 500ha's depending on variability of soil).	Great to hear that there's a match there. Thanks for sharing . -N/A required-	
Sam Duncan, MSc., CEO at Farmlabs	- Great approach to modeling both SOC and Carbon T/Ha - I think there's going to be a lot of development over the near term around these models, so good to see the method takes this into account and leaves room for new techniques. Well done.	We appreciate it. -N/A required-	

Sam Duncan, MSc., CEO at Farmlabs	- Instead of 'clipping' the uppermost value of the model to the uppermost value of the actual data, it may be better to krig all the residuals of the soil test results back to the model. This gets around the issue of 'clipping' to the upper most value, but having that value appear numerous times across the spatial data despite the on ground sample contradicting it. E.g. I may have an upper limit of 2% carbon across my samples (and model), however at some of the sites the model predicts 2% but measured they are 1.5%. Krigging this result back into the model will reduce the sample value at that location, retaining some of the spatial accuracy derived from the on ground measurements. See pg. 74 of the FAO's soil carbon cookbook for more info: https://www.fao.org/publications/card/es/c/20e8e2b0-8bcd-401c-be19-7b427316e9cb/	We decided to leave the clipping so there's more conservativeness in the results and less room for overestimation. Nonetheless we added the regression kriging option in several steps of the method and left some room for Monitors to decide on a better or alternative approach than the ones we suggest.	
Sam Duncan, MSc., CEO at Farmlabs	- Error deductions are good, I think all methods need this as it is hard to always get consistently accurate models, especially in areas that haven't had much sampling historically.	Agree! -N/A required-	

Sam Duncan, MSc., CEO at Farmlabs	- The only final thing I think may be missing (although you could capture it somewhere else outside the method) is the need to monitor 'leakage'. The Australian Regulator is starting to consider leakage in projects, whereby for example a proponent decides to move all the stock out of their project area but shift them to a part of the farm that isn't part of the project, and intensively graze this. Whilst carbon may increase in the project area, it's being done at the expense of carbon on another part of the farm. The Australian Method's new approach (currently out for review) is actually to measure the entire farm to calculate Net Change in soil carbon, but only credit only the project. These two areas are termed the 'Non Creditable Carbon Estimation area' (NCCEA) and the 'Creditable Carbon Estimation Area' (CCEA). Worth considering if it's not covered outside the method, but obviously more costly to implement/enforce. N.B. These areas don't include buildings or parts of the farm <1ha to avoid unnecessary sampling/costs.	We refreshed this section in the Credit Class document, to effectively address and mitigate the potential for emissions leakage. We now specify that a lookback period of 3 years is used to calculate business as usual average livestock number of heads. Then , if any reductions by more than 10% in the number of heads during the monitoring period occur, the GHG emissions from the livestock that was presumably relocated needs to be taken into account. .	

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	Well done, good to see lots of development in the method either way.		
Hugh Sturrock, Ph.D, Co-Founder and CEO at Loamin	I can understand the rationale for looking at error at the soil observation level (i.e. difference between observed and predicted values) and using this as a deduction, but I think a better approach is to estimate the uncertainty around the project level mean carbon stock. If you do this at each time point, then it is possible to statistically test whether change has occurred. Estimating uncertainty at the project level from pixel level predictions isn't simple, as you need to account for so called spatial 'autocorrelation' (which essentially means that two measurements near to each other are more similar to measurements further apart). But, there are geostatistical approaches that are built for this. There is a recent paper on this which outlines one such approach https://besjournals.onlinelibrary.wiley.com/doi/…. We are building some tools to automate	Thanks for this feedback, once again. For uncertainty assessments we shifted the text so we now allow the expert monitor to choose a better analysis approach. We also added the approach from the paper you referenced as an alternative.	

	the whole modeling process, including generating estimates of uncertainty, to simplify it for project developers. Happy to discuss with anyone interested!		
Martijn Witjes, Ph. D. OpenGeo Hub	Step 1: Creating the SOC% Raster: The distinction between regression and other machine learning is not correct; regression models are also fit to data and used to make predictions, and are in effect also machine learning techniques. I recommend saying 'several machine learning techniques are possible' and then listing basic regression, boosting, random forests, and deep learning, as these are the most used in remote sensing and soil mapping. Also, not all machine learning models need large training datasets.	We appreciate this comment, we now corrected the text so the regression reads as an alternative ML. We also reworded it to comply with your observation that not all machine learning models need large training datasets.	
Martijn Witjes, Ph. D. OpenGeo Hub	Step 2: Creating the bulk density raster I would advise including regression kriging in the listed methods. It combines machine learning with spatial statistics and is generally well-received and more powerful. Also, there's a typo in the accompanying figure:	We added regression kriging as an explicit option for interpolation of BD. We also corrected the typo and simplified the text according to your comment. Thanks!	

	I think you could simplify the part by simply saying that you can/will use several machine learning techniques. Usually, you need to try several to simply see which one makes the best maps.		