Carbon: Where is it and how can we know?

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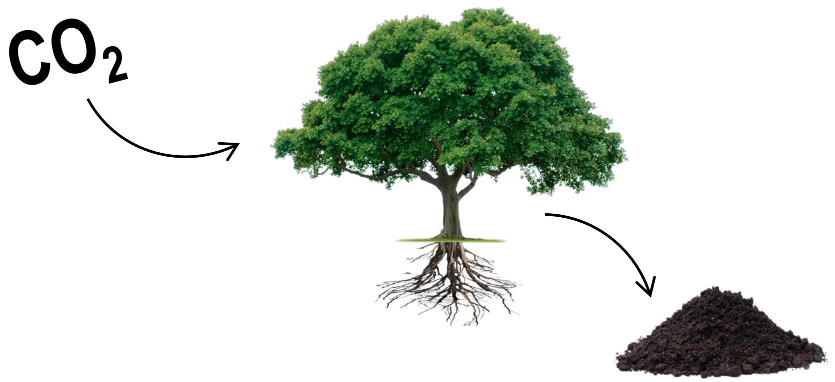
EPA Renewable Fuel Standard Program | Workshop on Biofuel Greenhouse Gas Modeling
February 28th, 2022

Image: National Biomass Carbon Dataset 2000

"Carbon": What do we mean and why does it matter?

Carbon is embodied in the biomass of plants (above and below ground) and in soil organic matter.



Relevance to biofuels: changes to carbon stocks incited either directly or indirectly by biofuel production are attributable to the greenhouse gas balance of those fuels.

To estimate these effects and properly evaluate the GHG balance of biofuels, we must know where carbon stocks are located and in what quantities.

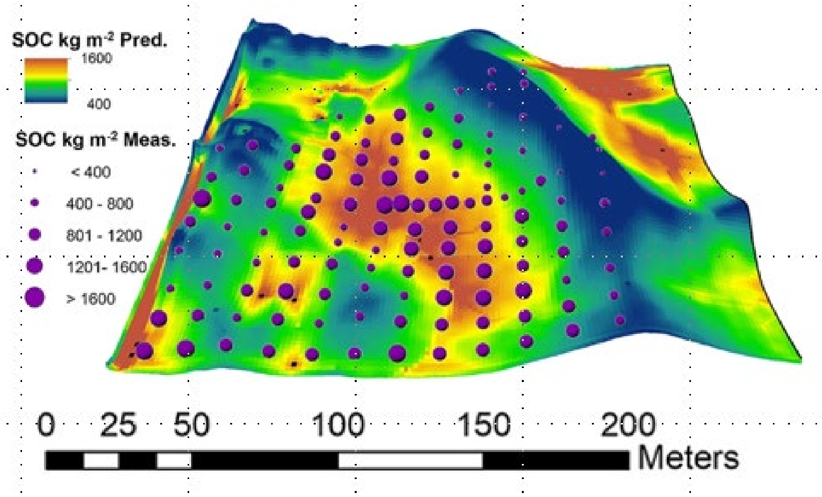
The data sources we use to assess carbon changes depend on the scale and scope of our analysis.

Finest scales: [in]direct measurements

At the finest scales we can directly measure carbon stocks: harvest and analyze.

But field data are often actually indirect measurements…
- Inferred from more easily acquired, non-destructive measurements.
  (e.g., Allometry based on tree height or diameter; root-to-shoot ratios; etc.)

Carbon stocks vary tremendously, even in close proximity
- A single measurement is not likely representative of its surroundings.
- Many samples are needed to generate confident averages
  (Conant & Paustian, 2002; Vanguelova et al., 2016)



(Li et al., 2018)

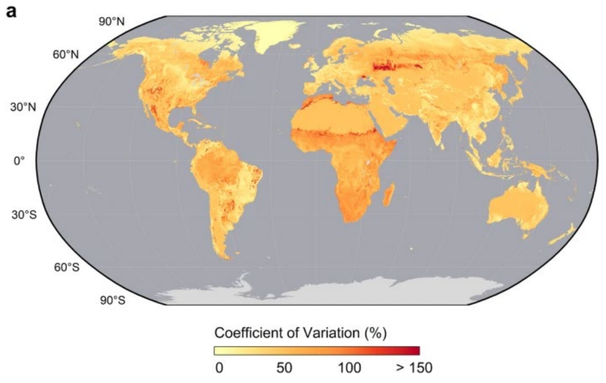
Field averages are the data used to both make and assess the accuracy/uncertainty of our maps and models.

Measures of [un]certainty

CONFIDENCE

"How much do measurements/estimates vary when repeated?"

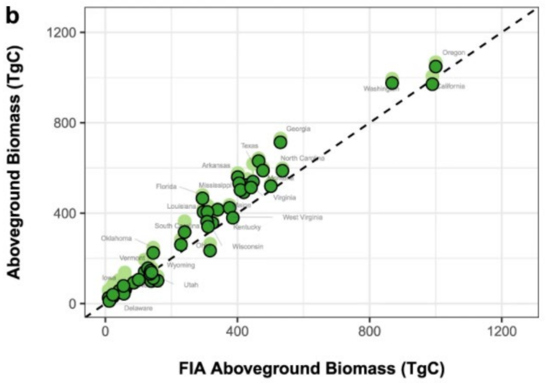
e.g., Expressed as the standard deviation of a mean



ACCURACY

"How well do predictions match independent, [in]direct measurements?"

e.g., Expressed as Root Mean Square Error (RMSE).



Figures: Spawn et al., 2020

Scaling up: class averages

Field measurements can be aggregated by category, and their average used to infer stocks elsewhere.

Examples:

- IPCC Tier 1 method – "default values"
- In biofuel LCA modelling:
  - "AEZ" emissions factors
  - "Woods Hole" emissions factors
  - "Winrock" emissions factors

Pitfalls:

- Often based on very small samples
- Assumes uniformity of stocks within a class
- Highly uncertain (whether explicit or not)
- Often biased by sampling scheme
  - (Powers et al., 2011, Langner et al., 2014)

Example: IPCC biomass defaults for young secondary forests in North America (IPCC, 2019)

Eco-zone	Stock (t/ha)	Confidence (CV)
Mountain	58	**136%**
Continental	46	**216%**
Oceanic	214	**106%**
Desert	26	**137%**
Steppe	43	**178%**

Mapping: “paint by number”

Class averages can be mapped if we know the locations of classes for which we have averages.

Landcover Map:

Grass	Grass	Savanna
Grass	Savanna	Forest
Savanna	Forest	Forest

+

Biome Averages:

Biome	C Stock
Grass	5 tC/ha
Savanna	30 tC/ha
Forest	100 tC/ha

=

Carbon Map (tC/ha):

5	5	30
5	30	100
30	100	100

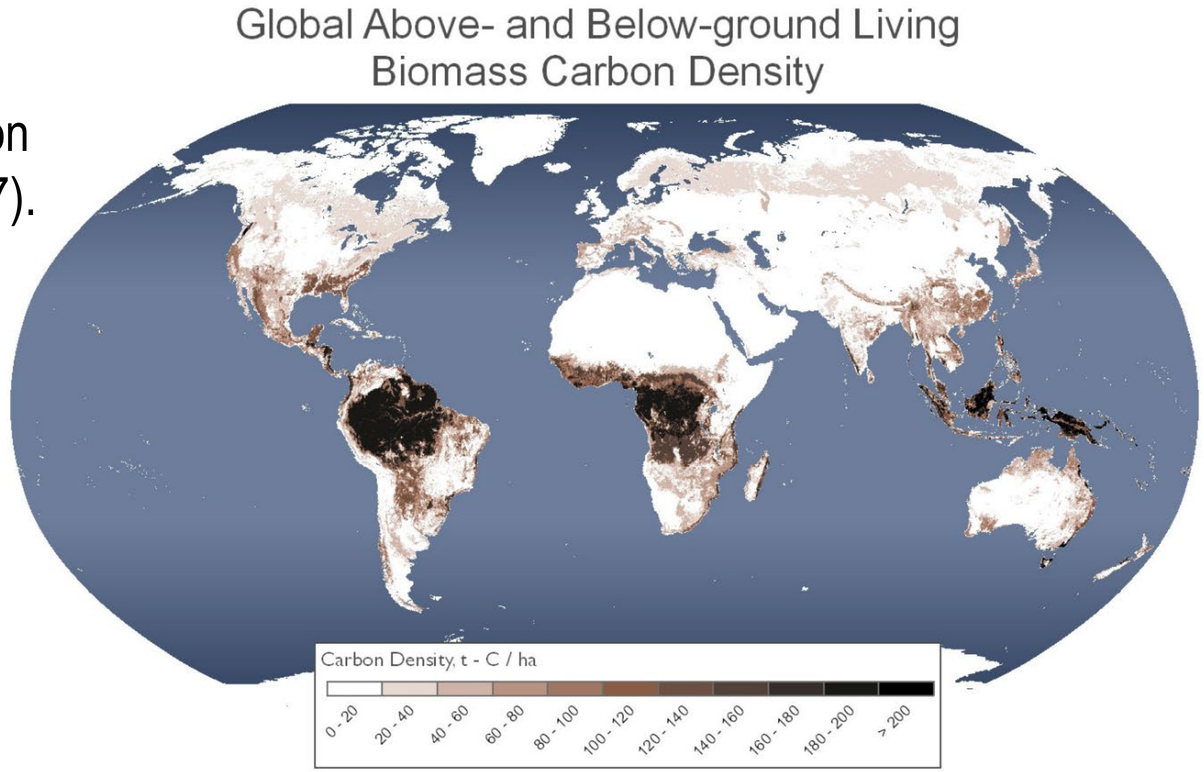
Pitfalls:

- All those associated with averages, plus:
- No variation within classes
- Limited by the quality of the landcover map
- Uncertainty rarely noted
- Artificial edge effects from mapped class boundaries
- Voids where data isn’t available
- Temporal and thematic inconsistencies
- Etc.

Mapping: “paint by number” (biomass)

Class averages can be mapped if we know the locations of classes for which we have averages

Basis for the IPCC Tier-1 Global Biomass Carbon Map for the Year 2000 (Ruesch and Gibbs, 2007).

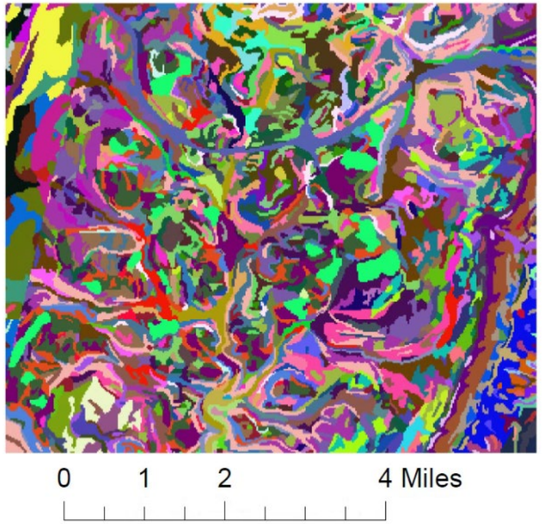


Mapping: “paint by number” (soil)

“Paint by number” has also long been used for soil mapping.

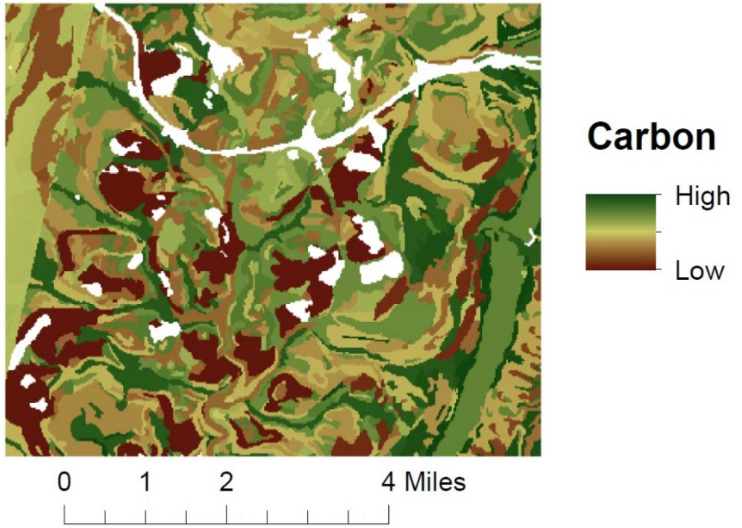
- In soil applications, its often more data-intensive and better resolved.
- Uncertainty is still rarely reported.

Soil Type Map:



SSURGO (Soil Survey Staff, 2016)

Soil Carbon Map:

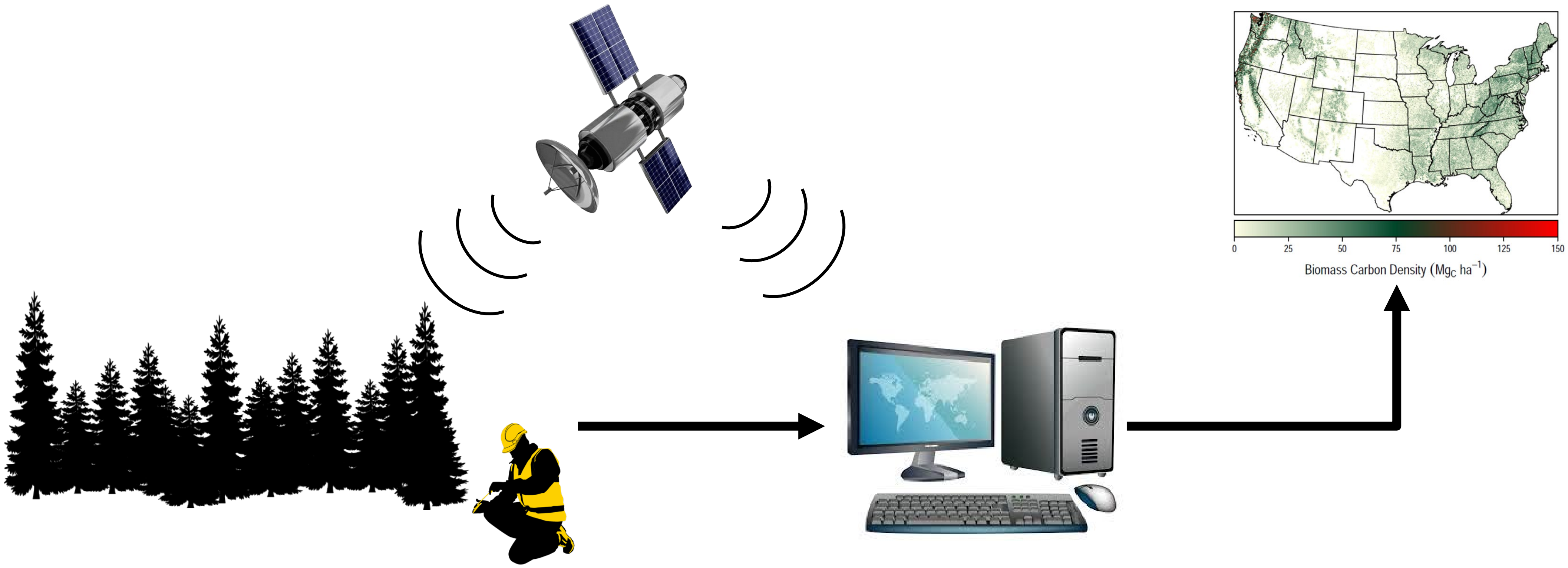


Example Datasets:
(order: finest to coarsest resolution)

- SSURGO or NATSGO (USA) (e.g., Soil Survey Staff, 2016)
- STATSGO (USA) (West, 2014)
- Harmonized World Soils Database (GLOBAL) (FAO, 2009)

Mapping: Statistical Approaches

Statistical relationships between field measurements and mapped variables are identified and then used to predict stocks throughout space.

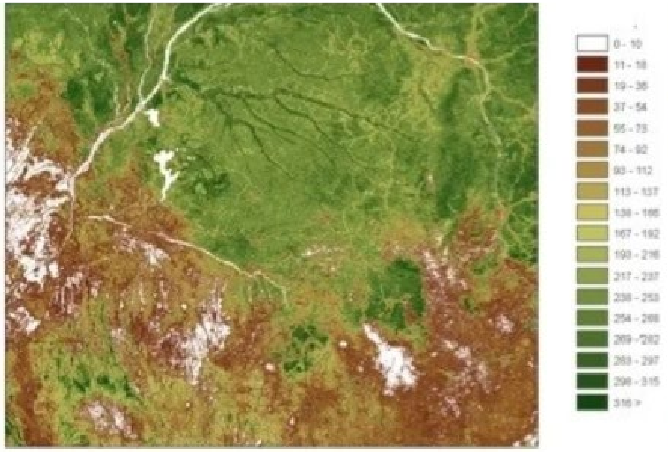


Mapping: Statistical Approaches

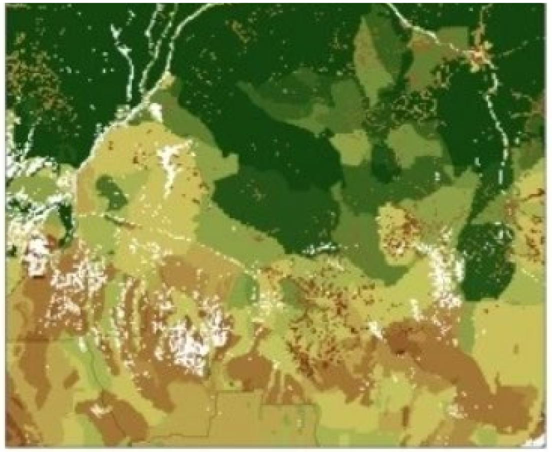
Promises:

- Spatially consistent
- Spatially continuous
- Far more spatially resolved
- [Often] based on direct observations
- Easily updateable
- Uncertainty is more readily quantified

Machine Learning:



Paint by Number:



(from: Goetz et al., 2009)

Pitfalls:

- Only as good as the data its given
- Computationally and data intensive
- Can't explicitly account for unseen factors like land use history (soil)

Mapping: Statistical Approaches (biomass)

Machine learning *à la* 'remote sensing' has been the 'state of the art' of forest biomass mapping for decades.

Various types of remotely sensed imagery used:

Imagery Type:	Measuring	Record Length	Systematic Issues
Optical Reflectance	Reflectance/Color	Long	Saturates in areas of dense biomass
Synthetic Aperture Radar (SAR)	Surface Texture	Long	Sensitivity varies with biomass density
LiDAR	Plant Height/Structure	Short	Previously sparse coverage.

Accuracy of biomass maps has improved as combined use of different imagery types has become more common.

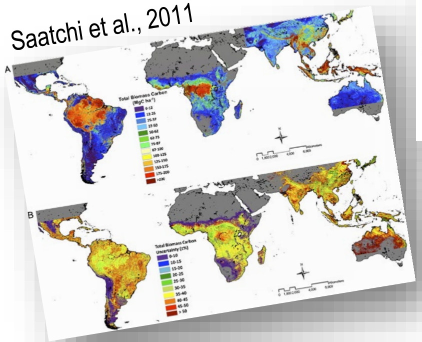
Burgeoning LiDAR records are expected to further improved accuracy.

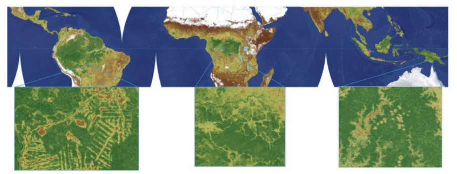
(Goetz et al., 2009, Xiao et al., 2019)

Mapping: Statistical Approaches (biomass)

There are many remotely-sensed biomass maps available (non exhaustive sample):

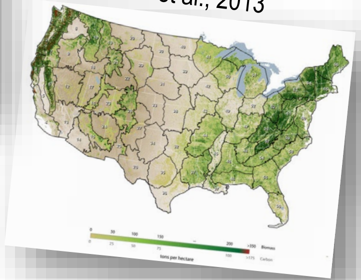
Saatchi et al., 2011



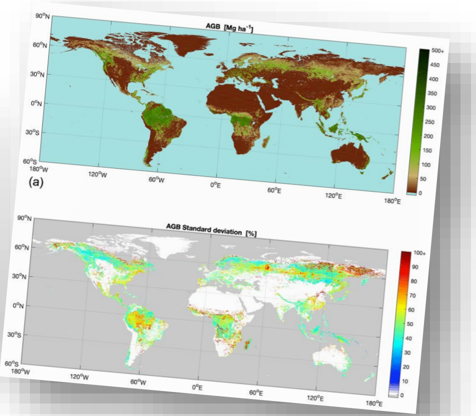


Baccini et al., 2012

Kellndorfer et al., 2013



Hurtt et al., 2019



Santoro et al., 2021

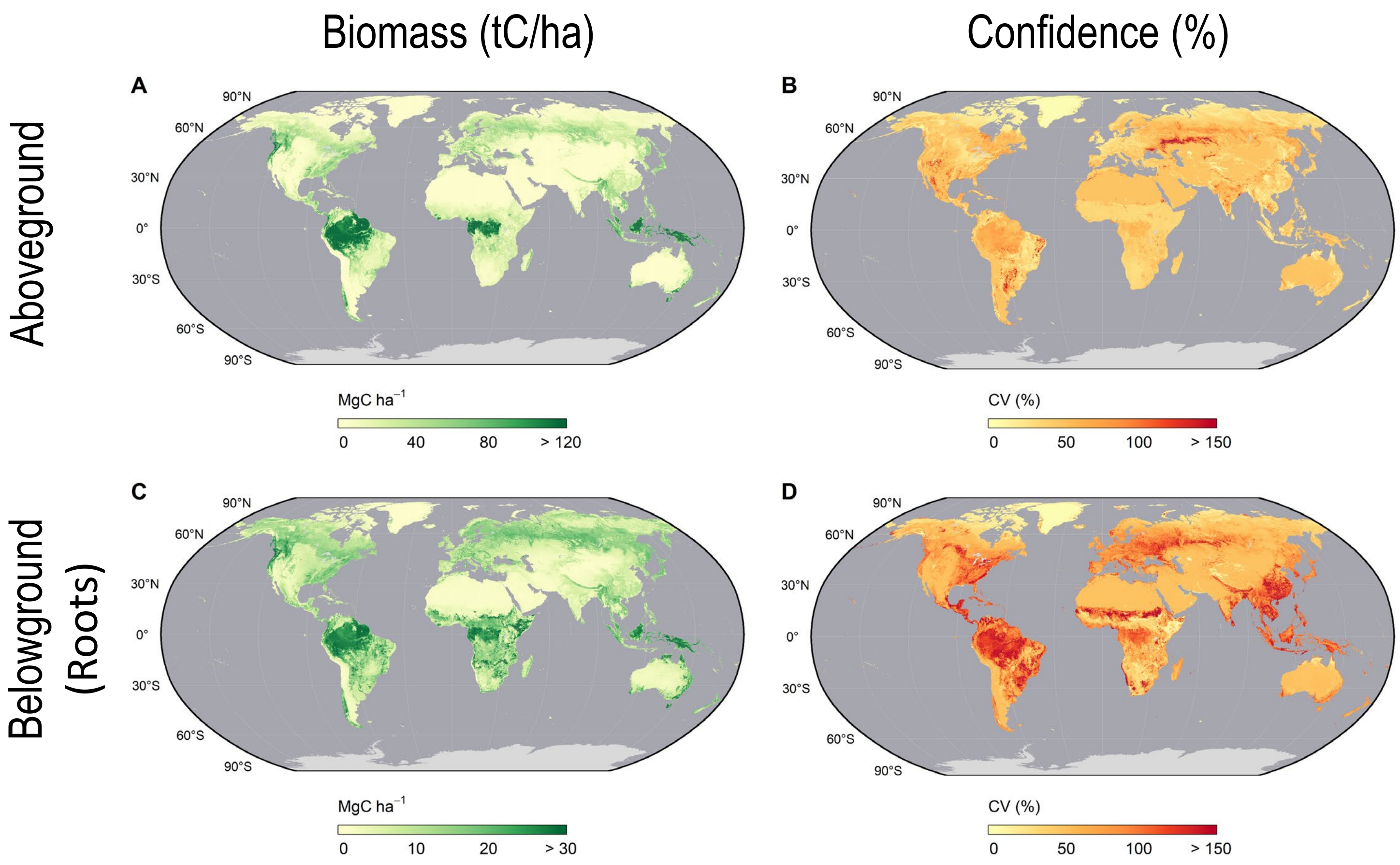
Wide range of scope and resolution; all include accuracy stats (many also with maps of pixel confidence)
Also: <u>Annual</u> 30m resolution global forest biomass maps (e.g., Baccini et al., 2017)—Direct obs. of carbon changes.

…BUT:

- *Remotely sensed biomass maps only represent <u>aboveground</u> biomass (i.e., they exclude root biomass).*
- *Typically, only report the biomass of a <u>single type of vegetation</u> (usually trees)*

Mapping: Statistical Approaches (biomass)

Solution? Harmonize and combine maps of above and below ground biomass *<u>and their confidence</u>* across a range of vegetation types; all representing conditions in the same year.



(Spawn et al., 2020)

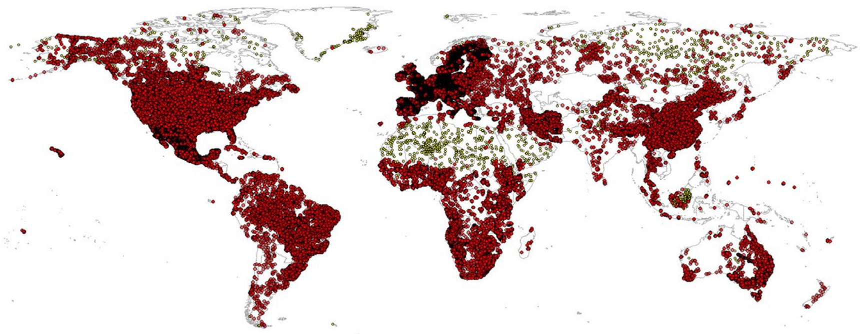
Mapping: Statistical Approaches (soil)

Recently, machine learning methods have also infiltrated soil carbon mapping

The challenge: Unlike aboveground biomass, soil can't typically be directly observed from space.

The answer: Use similar algorithms but with <u>much more and diverse data</u>.

- More field measurements
- Use imagery **+** maps of relevant variables:
  - Climate
  - Physiography
  - Soil properties
  - Land use
  - Etc.

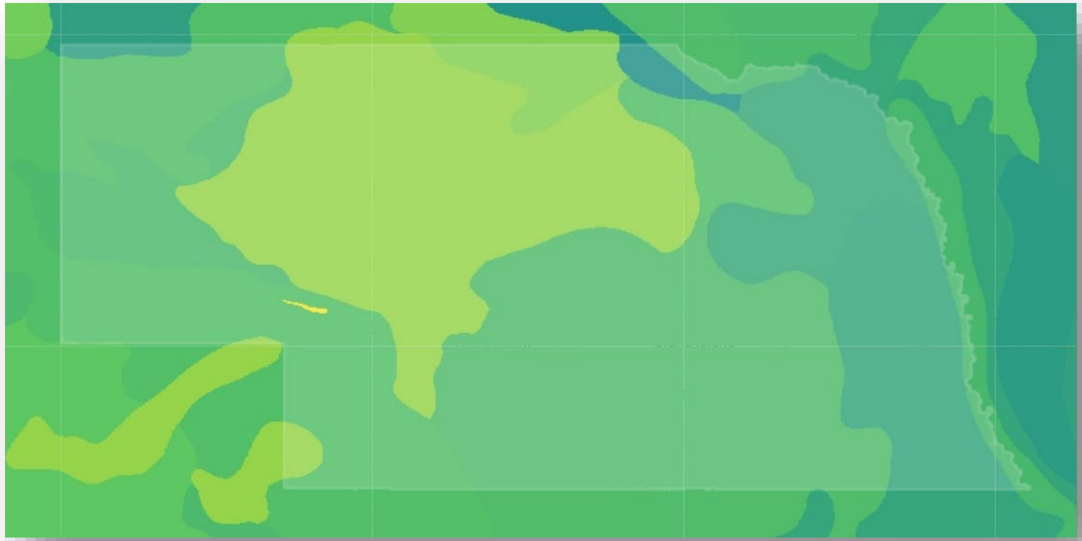


Locations of 150,000 field measurements used by Hengl et al., 2017

A recent global soil mapping effort used more than 240,000 field measurements and 400 global maps/images (Poggio et al., 2021).
(for comparison: global biomass efforts typically use <10,000 field measurements and 10s of global images)

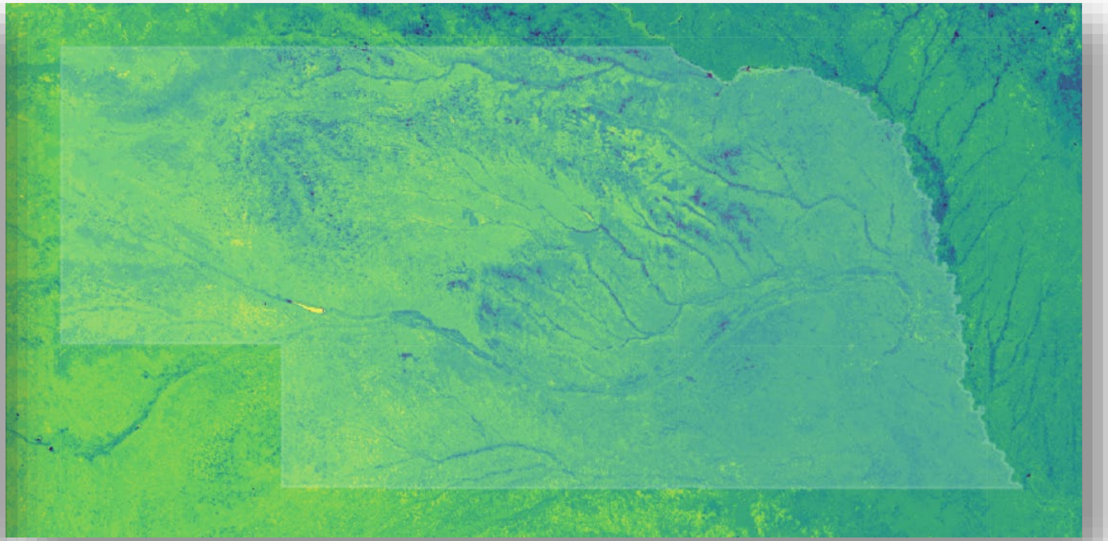
Mapping: Statistical Approaches (soil)

Harmonized World Soils Database (paint by number):



Wieder et al., 2014

Open Land Map (machine learning):



Hengl et al., 2018

- Machine learning results in more finely resolved predictions, revealing patterns not seen in courser maps.
- Finer scale predictions can more meaningfully be compared to field measurements to assess accuracy.

Mapping: Statistical Approaches (soil)

There are many soil carbon maps that have been produced via machine learning (non exhaustive sample):

Global Coverage:

Name	Release	Reference	Note
SoilGrids1km	2014	Hengl et al., 2014	[superseded]
SoilGrids250m	2017	Hengl et al., 2017	[superseded]
OpenLandMap	2018	Hengl and Wheeler, 2018	
SoilGrids2.0	2021	Poggio et al. 2021	

Also…

USA Coverage:
SoilGridsUSA (Ramcharan et al., 2018)

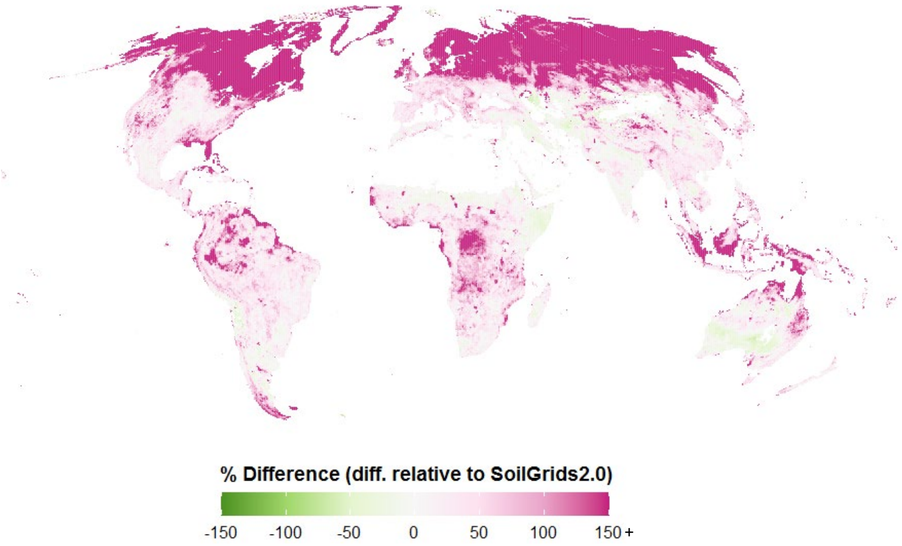
Earlier versions of SoilGrids [highly] (e.g., Hengl et al., 20xx) overestimated carbon stocks in peat and permafrost

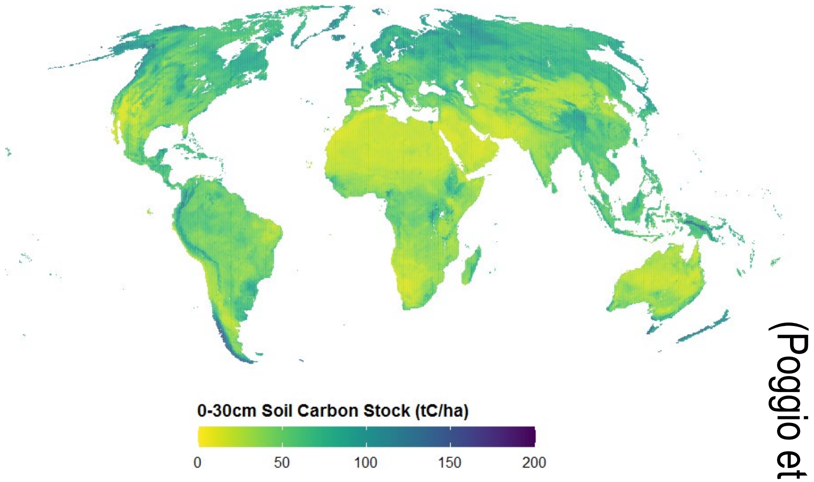
SoilGrids2.0 (i.e., Poggio et al., 2021) appears to have resolved these issues.

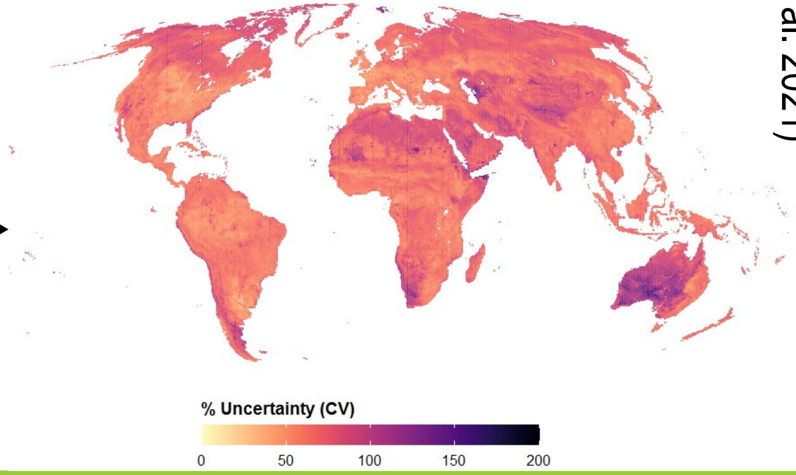
Mapping: Statistical Approaches (soil)

SoilGrids2.0 is the first to be accompanied by pixel level confidence estimates.

There remains substantial disagreement between SoilGrids2.0 and Open Land Map in some areas:







SoilGrids2.0
(Poggio et al. 2021)

Model Simulations (soil)

Rather than using existing carbon data, biophysical models often generate (i.e., “spin-up”) their own stock predictions by simulating soil development under a prescribed land use history.

Advantage: Can simulate less-visible factors like legacy management that observational approaches may miss.

Challenges:

- Computational burdens often necessitate coarser thematic and spatial resolution.
- The confidence and accuracy of model predictions are often <u>not</u> assessed due to computational burdens.
  - Model predictions often go unverified and can falsely-imply high degrees of certainty.
- Predicted carbon stocks [and fluxes], can be very sensitive to the quality of input data and assumptions.

Note: Studies using simulation models to estimate land use change emissions rarely report the initial stocks they spin up, making it difficult resolve disagreement among studies.

Take Homes:

There is no perfect carbon data – what's best depends on an application's scale and scope.

All carbon data sources are uncertain to varying degrees—whether noted or not.

- Biofuel LCAs have typically used very rudimentary carbon data that lag the accuracy and certainty of newer data sources.
- Newer data sources are typically more accurate, better resolved, and more transparent about their uncertainties.
- Simulation models can address the invisible, but their computational demands require tradeoffs and often precludes uncertainty estimation.

My recommendations:

- Evaluate, track, and report data/model uncertainty and favor sources and methods that enable transparency.
- Consider using ensemble approaches that employ multiple data sources to represent the same stocks.
- Look to examples being set elsewhere in the relevant sciences:
  - Innovative data and methods (e.g., Baccini et al. 2017, Harris et al. 2021, Hong et al. 2021, etc.).
  - Honest and productive treatment of data/model uncertainty/disagreement (e.g., Grassi et al. 2008, Ogle et al., 2010, Wallach et al. 2018, etc.).

Data Sources Referenced

Biomass Carbon Datasets:

- Baccini, A., Goetz, S.J., Walker, W.S., Laporte, N.T., Sun, M., Sulla-Menashe, D., Hackler, J., Beck, P.S.A., Dubayah, R., Friedl, M.A., Samanta, S., Houghton, R.A., 2012. Estimated carbon dioxide emissions from tropical deforestation improved by carbon-density maps. Nature Climate Change 2, 182–185. https://doi.org/10.1038/nclimate1354
- Baccini, A., Walker, W., Carvalho, L., Farina, M., Sulla-Menashe, D., Houghton, R.A., 2017. Tropical forests are a net carbon source based on aboveground measurements of gain and loss. Science 358, 230–234. https://doi.org/10.1126/science.aam5962
- Hurtt, G., Zhao, M., Sahajpal, R., Armstrong, A., Birdsey, R., Campbell, E., Dolan, K., Dubayah, R., Fisk, J.P., Flanagan, S., 2019. Beyond MRV: high-resolution forest carbon modeling for climate mitigation planning over Maryland, USA. Environmental Research Letters 14, 045013.
- IPCC, 2019. 2019 Refinement to the 2006 IPCC Guidlines for National Greenhouse Gas Inventories. IPCC National Greenhouse Gas Inventories Programme, Japan.
- Kellndorfer, J., Walker, W., Kirsch, K., Fiske, G., Bishop, J., Lapoint, L., Hoppus, M., Westfall, J., 2013. NACP Aboveground Biomass and Carbon Baseline Data, V.2 (NBCD 2000), U.S.A., 2000. https://doi.org/10.3334/ORNLDAAC/1161
- Ruesch, A., Gibbs, H., 2008. New IPCC Tier-1 Global Biomass Carbon Map for the Year 2000 [WWW Document]. Carbon Dioxide Information Analysis Center, Oak Ridge National Laboratory. URL http://cdiac.ess-dive.lbl.gov (accessed 1.18.18).
- Saatchi, S.S., Harris, N.L., Brown, S., Lefsky, M., Mitchard, E.T.A., Salas, W., Zutta, B.R., Buermann, W., Lewis, S.L., Hagen, S., Petrova, S., White, L., Silman, M., Morel, A., 2011. Benchmark map of forest carbon stocks in tropical regions across three continents. PNAS 108, 9899–9904. https://doi.org/10.1073/pnas.1019576108
- Santoro, M., Cartus, O., Carvalhais, N., Rozendaal, D.M.A., Avitabile, V., Araza, A., de Bruin, S., Herold, M., Quegan, S., Rodríguez-Veiga, P., Balzter, H., Carreiras, J., Schepaschenko, D., Korets, M., Shimada, M., Itoh, T., Moreno Martínez, Á., Cavlovic, J., Cazzolla Gatti, R., da Conceição Bispo, P., Dewnath, N., Labrière, N., Liang, J., Lindsell, J., Mitchard, E.T.A., Morel, A., Pacheco Pascagaza, A.M., Ryan, C.M., Slik, F., Vaglio Laurin, G., Verbeeck, H., Wijaya, A., Willcock, S., 2021. The global forest above-ground biomass pool for 2010 estimated from high-resolution satellite observations. Earth System Science Data 13, 3927–3950. https://doi.org/10.5194/essd-13-3927-2021
- Spawn, S.A., Sullivan, C.C., Lark, T.J., Gibbs, H.K., 2020. Harmonized global maps of above and belowground biomass carbon density in the year 2010. Scientific Data 7, 1–22. https://doi.org/10.1038/s41597-020-0444-4

Soil Carbon Datasets:

- FAO, 2009. Harmonized world soil database v1.2 | FAO SOILS PORTAL | Food and Agriculture Organization of the United Nations.
- Hengl, T., Jesus, J.M. de, Heuvelink, G.B.M., Gonzalez, M.R., Kilibarda, M., Blagotić, A., Shangguan, W., Wright, M.N., Geng, X., Bauer-Marschallinger, B., Guevara, M.A., Vargas, R., MacMillan, R.A., Batjes, N.H., Leenaars, J.G.B., Ribeiro, E., Wheeler, I., Mantel, S., Kempen, B., 2017. SoilGrids250m: Global gridded soil information based on machine learning. PLOS ONE 12, e0169748. https://doi.org/10.1371/journal.pone.0169748
- Hengl, T., Jesus, J.M. de, MacMillan, R.A., Batjes, N.H., Heuvelink, G.B.M., Ribeiro, E., Samuel-Rosa, A., Kempen, B., Leenaars, J.G.B., Walsh, M.G., Gonzalez, M.R., 2014. SoilGrids1km — Global Soil Information Based on Automated Mapping. PLOS ONE 9, e105992. https://doi.org/10.1371/journal.pone.0105992
- Hengl, T., Wheeler, I., 2018. Soil organic carbon stock in kg/m2 for 5 standard depth intervals (0–10, 10–30, 30–60, 60–100 and 100–200 cm) at 250 m resolution. https://doi.org/10.5281/zenodo.2536040
- Ramcharan, A., Hengl, T., Nauman, T., Brungard, C., Waltman, S., Wills, S., Thompson, J., 2018. Soil Property and Class Maps of the Conterminous US at 100 meter Spatial Resolution based on a Compilation of National Soil Point Observations and Machine Learning. Soil Science Society of America Journal 82, 186. https://doi.org/10.2136/sssaj2017.04.0122
- Soil Survey Staff, 2016. Gridded Soil Survey Geographic (gSSURGO) Database for the Conterminous United States.
- West, T.O., 2014. Soil Carbon Estimates in 20-cm Layers to 1-meter Depth, Conterminous US, 1970-1993 141.696259 MB. https://doi.org/10.3334/ORNLDAAC/1238
- Wieder, W.R., Boehnert, J., Bonan, G.B., Langseth, M., 2014. Regridded Harmonized World Soil Database v1.2 59.234908 MB. https://doi.org/10.3334/ORNLDAAC/1247

Studies Referenced

- Conant, R.T., Paustian, K., 2002. Spatial variability of soil organic carbon in grasslands: implications for detecting change at different scales. Environmental Pollution 116, S127–S135. https://doi.org/10.1016/S0269-7491(01)00265-2
- Goetz, S.J., Baccini, A., Laporte, N.T., Johns, T., Walker, W., Kellndorfer, J., Houghton, R.A., Sun, M., 2009. Mapping and monitoring carbon stocks with satellite observations: a comparison of methods. Carbon Balance and Management 4, 2. https://doi.org/10.1186/1750-0680-4-2
- Grassi, G., Monni, S., Federici, S., Achard, F., Mollicone, D., 2008. Applying the conservativeness principle to REDD to deal with the uncertainties of the estimates. Environ. Res. Lett. 3, 035005. https://doi.org/10.1088/1748-9326/3/3/035005
- Harris, N.L., Gibbs, D.A., Baccini, A., Birdsey, R.A., de Bruin, S., Farina, M., Fatoyinbo, L., Hansen, M.C., Herold, M., Houghton, R.A., Potapov, P.V., Suarez, D.R., Roman-Cuesta, R.M., Saatchi, S.S., Slay, C.M., Turubanova, S.A., Tyukavina, A., 2021. Global maps of twenty-first century forest carbon fluxes. Nat. Clim. Chang. 11, 234–240. https://doi.org/10.1038/s41558-020-00976-6
- Hong, C., Burney, J.A., Pongratz, J., Nabel, J.E.M.S., Mueller, N.D., Jackson, R.B., Davis, S.J., 2021. Global and regional drivers of land-use emissions in 1961–2017. Nature 589, 554–561. https://doi.org/10.1038/s41586-020-03138-y
- Langner, A., Achard, F., Grassi, G., 2014. Can recent pan-tropical biomass maps be used to derive alternative Tier 1 values for reporting REDD+ activities under UNFCCC? Environ. Res. Lett. 9, 124008. https://doi.org/10.1088/1748-9326/9/12/124008
- Li, X., McCarty, G.W., Karlen, D.L., Cambardella, C.A., Effland, W., 2018. Soil Organic Carbon and Isotope Composition Response to Topography and Erosion in Iowa. Journal of Geophysical Research: Biogeosciences 123, 3649–3667. https://doi.org/10.1029/2018JG004824
- Ogle, S.M., Breidt, F.J., Easter, M., Williams, S., Killian, K., Paustian, K., 2010. Scale and uncertainty in modeled soil organic carbon stock changes for US croplands using a process-based model. Global Change Biology 16, 810–822. https://doi.org/10.1111/j.1365-2486.2009.01951.x
- Powers, J.S., Corre, M.D., Twine, T.E., Veldkamp, E., 2011. Geographic bias of field observations of soil carbon stocks with tropical land-use changes precludes spatial extrapolation. PNAS 108, 6318–6322. https://doi.org/10.1073/pnas.1016774108
- Vanguelova, E.I., Bonifacio, E., De Vos, B., Hoosbeek, M.R., Berger, T.W., Vesterdal, L., Armolaitis, K., Celi, L., Dinca, L., Kjønaas, O.J., Pavlenda, P., Pumpanen, J., Püttsepp, Ü., Reidy, B., Simončič, P., Tobin, B., Zhiyanski, M., 2016. Sources of errors and uncertainties in the assessment of forest soil carbon stocks at different scales—review and recommendations. Environ Monit Assess 188, 630. https://doi.org/10.1007/s10661-016-5608-5
- Wallach, D., Martre, P., Liu, B., Asseng, S., Ewert, F., Thorburn, P.J., van Ittersum, M., Aggarwal, P.K., Ahmed, M., Basso, B., Biernath, C., Cammarano, D., Challinor, A.J., De Sanctis, G., Dumont, B., Eyshi Rezaei, E., Fereres, E., Fitzgerald, G.J., Gao, Y., Garcia-Vila, M., Gayler, S., Girousse, C., Hoogenboom, G., Horan, H., Izaurralde, R.C., Jones, C.D., Kassie, B.T., Kersebaum, K.C., Klein, C., Koehler, A.-K., Maiorano, A., Minoli, S., Müller, C., Naresh Kumar, S., Nendel, C., O'Leary, G.J., Palosuo, T., Priesack, E., Ripoche, D., Rötter, R.P., Semenov, M.A., Stöckle, C., Stratonovitch, P., Streck, T., Supit, I., Tao, F., Wolf, J., Zhang, Z., 2018. Multimodel ensembles improve predictions of crop–environment–management interactions. Global Change Biology 24, 5072–5083. https://doi.org/10.1111/gcb.14411
- Xiao, J., Chevallier, F., Gomez, C., Guanter, L., Hicke, J.A., Huete, A.R., Ichii, K., Ni, W., Pang, Y., Rahman, A.F., Sun, G., Yuan, W., Zhang, L., Zhang, X., 2019. Remote sensing of the terrestrial carbon cycle: A review of advances over 50 years. Remote Sensing of Environment 233, 111383. https://doi.org/10.1016/j.rse.2019.111383