Wetland Implementation and Rice Cultivation in the Sacramento-San Joaquin Delta, San Francisco Estuary and the Coast of California – Methodology for Quantifying Greenhouse Gas Emissions Reductions, Version 1.0 – METHODS MODULES

Preface

The objective of this methodology is to describe quantification procedures for the reduction of greenhouse gas (GHG) emissions through conversion of land to wetlands and rice cultivation in the Sacramento-San Joaquin Delta, San Francisco Estuary and in coastal areas of California. The methodology has been written in a module format; Project Proponents can choose the applicable modules for their specific project and site. The Framework Module provides background and an over-arching description of the methodology requirements and modules. The remaining modules provide guidance for baseline and project scenario quantification, methods, modeling, calculation of uncertainty, and other quantification tools. Project Proponents should refer first to the Framework Module for applicability requirements and an outline of the specific modules necessary for their project type.

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(MM-W/R) Methodological Module for Estimation of Carbon Stock Changes and Emissions for Wetland and Rice Cultivation Projects in the San Francisco Estuary and Sacramento-San Joaquin Delta

Scope

This module provides direction for *ex-ante* and *ex-poste* estimation of soil carbon-stock changes and emissions for baseline and project conditions and data collection for inputs to biogeochemical models.

Applicability

This module is applicable for baseline conditions and project activities that include managed and tidal wetlands and rice cultivation in the San Francisco Estuary and Sacramento-San Joaquin Delta. The Framework Module (WR-MF) describes the applicable conditions and relevant project activities for the use of the methodology. If eddy covariance is used for project conditions, aqueous carbon losses from the wetland or contributions to the wetland must also be accounted for. Biogeochemical models documented in the peer-reviewed literature that are calibrated and validated for the project area can be used for estimating carbon stock changes for baseline and project conditions; the Model and Framework modules provide guidance for use of biogeochemical models.

Parameters and Estimation Methods

Table 1. Parameters, description and estimation methods.

Table 14a. Carbon stock changes

Parameter symbol	SI Unit	Description	Estimation methods
ΔC_{BSL}	Metric tons CO ₂ -e (t CO ₂ -e)	Cumulative total of carbon stock changes for the baseline scenario	 Biogeochemical modeling Eddy-covariance Subsidence measurements
ΔC_P	Metric tons CO2-e (t CO2-e)	Cumulative total of carbon stock changes for the project scenario	 Eddy-covariance Modeling Soil core collection and analysis using feldspar markers and tidal pins

Table 14b. Emissions

Parameter symbol	SI Unit	Description	Estimation methods
ΔGHG_{BSL}	Metric tons CO2-e (t CO2- e)	Cumulative net GHG emissions for the baseline scenario	 Chamber measurements Biogeochemical modeling Eddy-covariance measurements Subsidence measurements
ΔGHG_P	Metric tons CO ₂ -e (t CO ₂ - e)	Cumulative net GHG emissions due to project activities	 Chamber measurements Biogeochemical modeling Eddy-covariance measurements
E _{FFC}	Metric tons CO2-e (t CO2- e)	Cumulative GHG emissions due to combustion of fossil fuel	 Module <u>E-FFC-WR</u>, provides guidance for fossil fuel emissions estimates.



Figure 1. Relation of project and baseline activities to methods for determination of GHG emissions and soil carbon stock changes.

* LUE-DAMM and SUBCALC models are described in the MODEL Module.

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This module also provides guidance for determination of the following parameters, which are inputs for biogeochemical models for project conditions. These parameters can be estimated using appropriate measurements documented in the peer-reviewed literature or estimates from proxy systems. If proxy measurements are used, documentation of sufficiently similar climate, soil chemical, hydrologic conditions, and vegetation conditions are required.

Parameter	SI Unit	Description	Estimation methods
$\Delta C_{ag\ biomass\ P}$	Metric tons CO ₂ -e (t CO ₂ -e)	Cumulative above-ground non-woody biomass carbon stock changes for project	Allometric equations, leaf area index, digital photography, destructive methods
$\Delta C_{bg\ biomass\ P}$	Metric tons CO ₂ -e (t CO ₂ -e)	Cumulative below-ground biomass carbon stock changes for project	Multiplication of accumulated above-ground biomass times published root:shoot ratio, destructive methods
$\Delta C_{litter P}$	Metric tons CO ₂ -e (t CO ₂ -e)	Litter carbon stock changes	Direct measurements using decomposition bags or indirect estimates from isotopic technique and/or modeled estimates based on environmental controls
$\Delta C_{cr BSL}$	Metric tons CO ₂ -e (t CO ₂ -e)	Crop residue remaining in field for baseline conditions	Destructive methods for harvest and determination of carbon content of biomass.

Table 2. Parameters used in biogeochemical models, description and estimation methods.

Methods

Figure 3 and Table 14 show the appropriate methods for both the project and baseline activities. The 'appropriate methods' listed can be used alone or in tandem with the other methods listed. The selection of methods depends on project and baseline conditions, data availability, and the requisite level of certainty.

Each method listed below is discussed with an introduction, method-specific applicability conditions, quality control and assurance procedures, and method-specific equations:

- Eddy covariance
- Chamber measurements
- Harvested grain and biomass
- Aqueous Carbon Loads
- Subsidence measurements
- Soil coring

Additionally, methods used for inputs to biogeochemical models are outlined below.

Eddy Covariance

Introduction

The eddy covariance (EC) technique¹ estimates fluxes of GHGs by relying on the concurrent determination and statistical analysis of vertical atmospheric velocity and the atmospheric concentration of the GHG (e.g. CO₂, CH₄, N₂O) of interest. These two values (GHG concentration and vertical atmospheric velocity) are multiplied to obtain a flux. Carbon dioxide and methane (CH₄) can be measured at the field scales of tens of acres using this method. The eddy covariance method is capable of measuring gaseous fluxes directly and for extended periods of time in a quasi-continuous manner. This approach is allowed for estimating carbon stock changes and emissions for baseline and project conditions. Soil carbon stock changes can be quantified by measuring the net ecosystem carbon exchange.

Eddy covariance measurements provide an effective way to determine the net exchange of CO_2 for a variety of ecosystems and have been used to measure baseline² and project carbon stock changes on Delta organic and highly organic mineral soils.

For agricultural baseline conditions (e.g. corn) on organic soils, CO₂ assimilation occurs as the result of plant photosynthetic uptake during the growing season and the crop is a net GHG remover during this time. During the non-crop period, oxidation of organic matter results in a net GHG emission. However, CO₂ assimilation into the harvested grain is removed and results in an overall annual GHG emission for the cropped system under drained conditions. In contrast, for a permanently flooded wetland and to a lesser extent, rice, flooding the soil during the warmest time of the year greatly reduces GHG emissions due to oxidation of soil organic matter and there is net CO₂ assimilation into the wetland vegetation resulting in a net GHG removal.

Several researchers have used eddy covariance to measure the carbon budget for agricultural, marsh and forest ecosystems. Hatala et al.³ determined the rates of carbon stock changes in rice and a pasture on an organic soil in the Sacramento-San Joaquin Delta. Their rates of carbon capture in rice were slightly lower than those from a riparian cottonwood stand about 50 km east of their site where Kochendorfer et al.⁴ measured a net carbon removal using eddy covariance. The magnitude of CO₂ uptake at the Hatala et al. rice paddy was well below that from a restored marsh in southern California, where net carbon captured measured with eddy covariance varied between 6.8 and 18.5 tons CO₂ per acre during an eight-year study⁵, higher than historical rates of accumulation in disturbed ecosystems of

¹ Baldocchi DD, Hicks BB, Meyers TP (1988) Measuring biosphere–atmosphere exchanges of biologically related gases with micrometeorological methods. *Ecology* **69**, 1331–1340.

² Teh YA, Silver WL, Sonnentag O, Detto M, Kelly M, Baldocchi DD (2011) Large greenhouse gas emissions from a temperate peatland pasture. *Ecosystems* **14**, 311–325.

³ Hatala JA, Detto M, Sonnentag O, Deverel SJ, Verfaillie J, Baldocchi DD (2012) Greenhouse gas (CO₂, CH₄, H₂O) fluxes from drained and flooded agricultural peatlands in the Sacramento-San Joaquin Delta. *Agriculture, Ecosystems and Environment* **150**,1-18.

⁴ Kochendorfer J, Castillo EG, Haas E, Oechel WC, Paw UKT (2011) Net ecosystem exchange, evapotranspiration and canopy conductance in a riparian forest. *Agric.Forest Meteorol*. **151**, 544–553.

⁵ Rocha AV, Goulden ML (2008) Large interannual CO₂ and energy exchange variability in a freshwater marsh under consistent environmental conditions. *J. Geophys. Res. Biogeosci.* **113**, G03026

the same region⁶. Hollinger at al.⁷ used continuous eddy-covariance carbon flux measurements from 1997 to 2002 to evaluate the carbon budget for a maize and soybean rotation agricultural ecosystem. Their results indicated and net carbon sequestration of 7 and 0.5 metric tons CO_2 per acre per year for maize and soybean on mineral soils, respectively. However, these authors did not account for N₂O emissions.

Applicability Conditions

The following applicability conditions apply to the use of eddy covariance.

- <u>Stratification and eddy covariance footprint.</u> The area of land that is included in the footprint of the eddy covariance measurement shall be quantified during the monitoring period and shall be shown to adequately represent the hydrologic, water quality and soil conditions and management practices for the stratum. For example, for baseline conditions, the agricultural crop and water- and land-management practices within the eddy covariance footprint shall be the same as for the entire stratum. Also, for baseline conditions, the average soil organic matter content within the eddy-covariance footprint shall not vary more than 20 % relative to the average soil organic matter content within the stratum.
- 2. <u>Adjacent land uses</u>. To avoid influences of adjacent land uses, the eddy covariance footprint shall be entirely within the stratum that includes project or baseline land uses.
- 3. <u>Monitoring period</u>. The monitoring period using eddy covariance techniques shall be sufficient to quantify annual variations in carbon stock changes and to enable the use of biogeochemical models. The Project Proponents shall demonstrate that annual values for carbon stock changes for baseline are representative. At least one year of monitoring is required for baseline conditions. The baseline scenario shall be developed for the entire life of the project using site-specific data and/or data and models documented in the peer-reviewed literature. For project conditions, continuous monitoring is required throughout the life of the project unless the use of biogeochemical models calibrated with the eddy covariance data are shown to adequately predict emissions and carbon stock changes. At this point, eddy covariance measurements can be terminated.

Quality Control and Quality Assurance Procedures

⁶ Canuel EA, Lerberg EJ, Dickhut RM, Kuehl SA, Bianchi TS, Wakeham SG (2009) Changes in sediment and organic carbon accumulation in a highly disturbed ecosystem: the Sacramento-San Joaquin River Delta (California, USA). *Mar. Pollut. Bull.* **59**, 154–163.

⁷ Hollinger SE, Bernacchil CJ, Myers TP (2005) Carbon budget of mature no-till ecosystem in North Central Region of the United States, *Agricultural and Forest Meterology*, **130**, 59–69.

able of Quality control, assurance	for Eddy Cordinance medsarenn	
Quality Control/Assurance	Considerations	Procedures
Торіс		
Temporal variability and	GHG and energy fluxes shall	Standard eddy covariance practice as
frequency of measurements	be measured at each site	described in the literature cited above shall
	with the FC method ⁸ using	be employed to measure the covariance
	parameters determined to	between turbulence and C fluxes at 10 Hz
	parameters determined to	intervals (overy 0.1.s). These data shall be
		used to coloulate half hours funce for not
	eddy covariance	used to calculate nall-nourly fluxes for net
	measurements in peat soils	ecosystem exchange.
	and wetlands. Carbon	
	accumulation rates shall be	
	compared with	
	measurements reported for	
	natural and disturbed	
	ecosystems in the region.	
Filtering and removal of	Eddy covariance data	The sampling rate and averaging interval will
spurious data	typically contain gaps and	allow for a 5 Hz cut-off for the cospectra
	artificial snikes	between turbulence and carbon fluxes
	artificial spikes.	After computing the fluxes flux values with
		anomalously high and low friction velocity
		(ut > 1.2 m = 1 and lunul < 0.02) shall be
		$(u^{-} > 1.2 \text{ III S} - 1 \text{ and } uw < 0.02) \text{ shall be}$
		filtered to constrain the analysis to periods
		where the air near the sensors was well-
		mixed. The random instrumental noise in
		each half-hour fluxes shall be assessed using
		bootstrapping technique. Fluxes from wind
		directions outside of the footprint of the
		target land-use type shall be excluded from
		the dataset. For baseline and project
		conditions, missing data shall be treated
		conservatively so as to not overestimate the
		GHG benefit.
		Filtering software may be used to remove
		artificial spikes, which shall be greater than
		six standard deviations of the mean within a
		one-minute window and diagnostic
		instrument values that corresponded with
		had readings, which are often correlated
		with rain or fog events. Typically, no loss
		than 10% of the original flux data is
		avaluded through this presedure. The
		excluded through this procedure. The
		Project Proponents shall justify a
		conservative application of any larger
		percentages. The bootstrap technique will

Table 3. Quality Control/Assurance for Eddy Covariance Measurements.

⁸ Baldocchi DD, Hicks BB, Meyers TP (1988) Measuring biosphere–atmosphere exchanges of biologically related gases with micrometeorological methods. *Ecology* **69**, 1331–1340.

	evaluate the covariances to calculate the standard deviation of calculated fluxes across the bootstrapped covariances.

Equations

$$\Delta GHG = T_p * \left[\sum_{i=1}^{n} (E_{CO_2,i} + E_{CH_4,i} + E_{N_2O,i}) + \sum_{i=1}^{n} Cgr_i + E_{aq_i} \right]$$
(13)

where:

ΔGHG	is the cumulative net emissions of CO ₂ and CH ₄ during the reporting period (t CO ₂ -e);
E _{CO2} ,i	is the annual net emission of CO_2 (t CO_2 -e yr ⁻¹);
E _{CH4} ,i	is the annual net emission of CH_4 (t CO_2 -e yr ⁻¹);
$E_{N_2O,i}$	is the annual net emission of N_2O (t CO_2 -e.yr ⁻¹);
i	is the stratum within the project boundary;
n	is the number of strata within the project boundary;
E _{aq}	is the annual net aqueous loss of carbon in drainage water (t CO_2 -e yr ⁻¹);
T_p	is the period of time which corresponds to the project reporting period in (yr.); and
Cgr _i	is the carbon removal in harvested biomass in stratum i (t CO ₂ -e yr ⁻¹).

The net aqueous loss of dissolved and particulate organic carbon can be calculated by subtracting the aqueous carbon input from the aqueous carbon export. Specifically,

$$E_{aq} = \left(Q_{export} \times [TOC] - Q_{import} \times [TOC]\right)$$
(14)

Because eddy covariance measures the net ecosystem exchange,

$$\Delta GHG = \Delta C \tag{15}$$

Where ΔC is the cumulative carbon stock change.

(MM-W/R) (MODEL-W/R) (X-UNC) (TOOLS)

Chamber Measurements

Introduction

For project and baseline conditions, gaseous fluxes of CO_2 , CH_4 and N_2O from wetland surfaces and open water for project or for baseline conditions can be measured using the static chamber method^{9 10}. Measurements should ensure that temporal variations are accounted for, or be measured during the time of greatest anticipated flux in order to conservatively estimate net GHG emission reductions/removal enhancements. For agricultural baseline conditions, the chamber methods described in Livingston and Hutchinson¹¹, Mosier¹² and Rolston¹³ are applicable. Chambers described in Lindau are appropriate for project conditions.^{14,15,16,17}

Temperature inside the chamber shall be monitored. Gas must be mixed so that a concentration gradient does not occur. Mixing is normally accomplished by diffusion in small chambers, but a small fan may be required to ensure mixing in larger chambers. Gas samples are taken with plastic syringe and stainless steel hypodermic needles. Samples shall be collected at minimum at least three times to allow to allow a linear buildup of the concentration of the gas being measured) after chamber top placement. The overpressure created will ensure that atmospheric gases will not contaminate the sample gases. Silicone sealant is used to seal the injection hole in the rubber septum. The CH₄, CO₂, or N₂O concentrations of the gas samples can be measured on a gas chromatograph (GC). The flux of gases from the soil or wetland surface is calculated from the data obtained from the GC and can be then estimated using the equation:

 $f(gas) = \frac{v\Delta c}{A\Delta t}$ (16)

⁹ Livingston, G.P. and G.L. Hutchinson, 1995. Enclosure-based Measurement of Trace Gas Exchange: Application and Sources of Error. P. 14-51 In: P.A. Matson and R.C. Harris (eds.) Biogenic Trace Gases: Measuring Emissions from Soil and Water. Blackwell Science Ltd., London.

¹⁰ Klinger, L.F., Zimmerman, P.R., Greenberg, J.P., Heidt, L.E., and Guenther, A.B., 1994. Carbon Trace Gas Fluxes Along a Successional Gradient in the Hudson Bay Lowland. J. Geophys. Res. 99 (D1):1469–1494.

¹¹ Livingston, G.P. and G.L. Hutchinson, 1995. Enclosure-based Measurement of Trace Gas Exchange: Application and Sources of Error. P. 14-51 In: P.A. Matson and R.C. Harris (eds.) Biogenic Trace Gases: Measuring Emissions from Soil and Water. Blackwell Science Ltd., London.

¹² Hutchinson, G. L., and A. R. Mosier, Improved soil cover method for field measurement of nitrous oxide fluxes, *Soil Sci. Soc. Am. J.*, *45*, 311–316, 1981.

¹³ Rolston, D. E., Gas flux, in *Methods of Soil Analysis, Part 1, Agron.Monogr.*, vol. 9, edited by A. Klute, pp. 1103–1119, Am. Soc. of Agron. and Soil Sci. Soc. of Am., Madison, Wis., 1986.

¹⁴ Lindau, C.W., and R.D. DeLaune. 1991. Dinitrogen and nitrous oxide emission and entrapment in *Spartina alterniflora* saltmarsh soils following addition of N-15 labelled ammonium and nitrate. Estuarine Coastal Shelf Sci. 32:161–173. doi:10.1016/0272-7714(91)90012-Z.

¹⁵ Miller, R.L., Hastings, L., Fujii, R., 2000. Hydrologic treatments affect gaseous carbon loss from organic soils, Twitchell Island, California, October 1995-December 1997. U.S. Dept. of the Interior, U.S. Geological Survey, Sacramento, Calif.

¹⁶ Majumdar, D., 2013. Biogeochemistry of N₂O Uptake and Consumption in Submerged Soils and Rice Fields and Implications in Climate Change. Critical Reviews in Environmental Science and Technology 43, 2653-2684.

¹⁷ Linquist, B.A., Adviento-Borbe, M.A., Pittelkow, C.M., van Kessel, C., van Groenigen, K.J., 2012b. Fertilizer management practices and greenhouse gas emissions from rice systems: A quantitative review and analysis. Field Crops Research 135, 10-21.

where:

f	is the GHG gas flux (g gas m ⁻² s ⁻¹);
V	is the volume of chamber headspace (m ³ gas volume);
A	is the soil surface area (m ²); and

 $\Delta C/\Delta t$ is the change in gas concentration (g m⁻³ S⁻¹).

Locations of measurements shall be determined by known spatial variability and the required level of certainty. Chamber measurements shall account for heterogeneous landscapes within strata as described in Baseline and Project Modules. If present, baseline chamber measurements shall be conducted within upland and lowland areas, and drainage ditches¹⁸. Spatially weighted up-scaling methods are recommended for estimating annual GHG budgets across heterogeneous landscapes. Flux measurements shall be taken multiple times during the year for estimating seasonal or annual flux and temporal and spatial replication is important to reduce uncertainty.

Special care must be taken when estimating N₂O emissions using chambers. Fertilization and re-wetting events are especially important for N₂O budgets, where a single pulse event can account for >50% of the annual N₂O budget¹⁹. Therefore, in order to accurately estimate N₂O emissions using manual chambers, deployment must include fertilization, irrigation and precipitation events. These pulse events can encompass several days (1-30 days) and therefore must be evaluated at an appropriate time scale. Estimations of annual N₂O budgets from chamber measurements must account for the amount and frequency of fertilization, irrigation, and precipitation events in addition to lower-level N₂O emission rates that occur outside pulse events.

Applicability Conditions

The following applicability conditions apply to the use of chambers.

- 1. <u>Stratification</u>. The distribution of chamber measurement shall be shown to adequately represent the hydrologic, water quality and soil conditions and land- and water-management practices for the stratum.
- 2. <u>Monitoring period</u>. The monitoring period using chamber measurements shall be sufficient to quantify possible annual variations in emissions. The Project Proponents shall demonstrate that annual values for emissions for baseline are representative. At least one year of monitoring is required for baseline conditions. For project conditions, monitoring is required throughout the life of the project unless the use of biogeochemical models calibrated with site data are shown to adequately predict emissions. At this point, chamber measurements may be terminated.
- 3. When measuring N₂O emissions using chambers, deployment must include fertilization,

¹⁸ Teh, Y.A., Silver, W.L., Sonnentag, O., Detto, M., Kelly, M., Baldocchi, D.D., 2011. Large greenhouse gas emissions from a temperate peatland pasture. Ecosystems 14, 311–325. These authors demonstrated that drainage ditches can account for <5% of the land area and contribute more than 84% of CH₄ emissions and 37% of ecosystem GWP in a Delta peat-land pasture.

¹⁹ Wagner-Riddle C, Thurtell G, Kidd G, Beauchamp E, Sweetman R (1997) Estimates of nitrous oxide emissions from agricultural fields over 28 months. *Canadian Journal of Soil Science*, **77**, 135-144.

irrigation and precipitation events.

4. Monitoring must occur for baseline establishment and renewal. For project conditions, the monitoring frequency shall occur at least every 5 years for one year. Baseline field monitoring should be conducted seasonally for one year to determine the seasonal effects on greenhouse gas fluxes, or measurements can be made during the period of peak emissions (e.g., summer or fertilization events). Livingston and Hutchinson²⁰ and Crill et al.²¹ provide guidance for minimizing measurement and flux estimation error in chamber measurements. Also, it is important to account for microsites and spatial variability as discussed above.

Quality Control and Quality Assurance Procedures

Quality assurance and control measures for chamber measurements are listed and discussed in Table 17.

²⁰ Livingston, G.P. and G.L. Hutchinson, 1995. Enclosure-based Measurement of Trace Gas Exchange: Application and Sources of Error. P. 14-51 In: P.A. Matson and R.C. Harris (eds.) Biogenic Trace Gases: Measuring Emissions from Soil and Water. Blackwell Science Ltd., London.

²¹ Crill, P.M., Butler, J.H., Cooper, D.J., and Novelli, P.C., 1995, Standard analytical methods for measuring trace gases in the environment In: P.A. Matson and R.C. Harris (eds.) Biogenic Trace Gases: Measuring Emissions from Soil and Water. Blackwell Science Ltd., London.

Quality Control/Assurance Topic	Considerations	Precautions and safeguards	Reference footnote
Temperature	Ambient temperature should be preserved within the chamber. Solar heating of the enclosure surface can rapidly lead to increasing chamber temperatures	Minimize deployment times, use shading of opaque materials, monitor chamber temperature	69
Deployment - development of a disturbance free seal	Leakage can occur in unsaturated-zone soils especially during high winds.	Use weighted skirts around chambers and /or baffled, double- walled enclosures. Avoid high winds. Estimate leakage with a tracer gas	69, 70
Deployment – surface compaction	Artificial gradients and mass inflow can be induced by surface compaction from foot traffic. Water-saturated soils are particularly susceptible.	Use of designated walkways, remote gas withdrawal from chambers.	69
Deployment – vegetative disturbance	Disturbance of vegetation can affect exchange processes under study and influence plant mediated gas transport	Avoid cutting roots or severing stems and leaves	69
Field sample handling and processing	Sample container leakage and accuracy	Analyze gas samples within a few hours, analyze standards frequently	69
Laboratory analysis	Potential for analytical error	Follow acceptable analytical protocol for trace gas analysis	69
Flux estimation	Time for concentration change measurements, chamber dimensions	Minimize sources of variability in sampling handling and analysis using maximum possible measurement period and number of independent samples. Two samples are insufficient. Determine chamber volume precisely.	69
Spatial variability and stratification	Previous measurements in Delta rangelands have	Locations of measurements shall be	

Table 4. Quality Control/Assurance for Chamber Measurements

(MM-W/R) (MODEL-W/R) (X-UNC) (TOOLS)

demonstrated substantial	determined by known	
spatial variability.	spatial variability and	
, ,	the required level of	
	certainty. Chamber	
	measurements must	
	account for	
	heterogeneous	
	landscapes. Spatially-	
	weighted up-scaling	
	methods are	
	recommended for	
	estimating annual GHG	
	budgets across	
	heterogeneous	
	landscapes	

Equations

Cumulative GHG emissions for baseline (ΔGHG_{BSL})

Where chambers are used to estimate cumulative GHG emissions shall be estimated using the following equation.

$$\Delta GHG_{BSL} = \left(\frac{1}{n} \sum_{t=1}^{n} fGHG_{BSL,t}\right) \times T_{pp} \times CF \tag{17}$$

where:

ACUC	is the sumulative not CUC emissions for the baseline scenario (t	
$\Delta G \Pi G_{RSL}$, CO ₂ -ej,

 $fGHG_{P,t}$ is the rate of GHG emissions from the project area at monitoring event t prior to project activity (t CO₂-e per unit of time);

T _{pp}	is the period of time which corresponds to the pre-project reporting period (yr.);
n	is the number of baseline monitoring events;
t	is the monitoring event; and
CF	is the factor for converting from the measurement time scale to the time scale of T_{pp} .

The flux of greenhouse gases from the project area under baseline conditions at time *t* is:

$$fGHG_{BSL,t} = \sum_{i=1}^{n} fGHG_{CH_4_BSL,i,t} \cdot GWP_{CH_4} + \sum_{i=1}^{n} fGHG_{N_2O_BSL,i,t} \cdot GWP_{N_2O}$$
(18)²²

where:

- $fGHG_{BSL,t}$ is the rate of GHG emissions from the project area at monitoring event t prior to project activity, measured using chambers (t CO₂-e per unit of time);
- $fGHG_{CH_4_BSL,i,t}$ is the rate of CH₄ emissions from the project area in stratum *i* at monitoring event *t* (t CO₂-e per unit of time);
- GWP_{CH_4} is the global warming potential for CH₄ (per most recent version of the ACR Standard) (t CO₂-e);
- $fGHG_{N_2O_BSL,i,t}$ is the rate of N₂O emissions from the project area in stratum *i* at monitoring event *t* (t CO₂-e per unit of time);
- GWP_{N_2O} is the global warming potential for N₂O (per most recent version of ACR Standard) (t CO2-e);
- *n* is the number of strata within the project boundary;
- *i* is the stratum within the project boundary; and
- *t* is the monitoring event.

Cumulative GHG emissions for the project scenario (ΔGHG_p)

Where chambers are used, total project GHG emissions should be extrapolated from average instantaneous measurements using the following equation:

$$\Delta GHG_P = \left(\frac{1}{n} \sum_{t=1}^n fGHG_{P,t}\right) \times T_p \times CF \tag{19}$$

where:

 ΔGHG_P is the cumulative total of GHG emissions as a result of implementation of the project activity (t CO₂-e);

²² CO₂ emissions due to organic matter oxidation cannot easily measured straightforwardly using chambers.

- $fGHG_{P,t}$ is the rate of GHG emissions from the project area at monitoring event t, measured using chambers (t CO₂-e per unit of time);
- *n* is the number of monitoring events;
- t is the monitoring event;
- CF is the factor for converting from the measurement time scale to the time scale of T_p); and
- T_p is the period of time which corresponds to the project reporting period (yr.).

The flux of greenhouse gases from the project area under the project scenario at time t is:

$$fGHG_{P,t} = \sum_{i=1}^{n} fGHG_{CH_{4},i,t} \cdot GWP_{CH_{4}} + \sum_{i=1}^{n} fGHG_{N_{2}O_{i},i,t} \cdot GWP_{N_{2}O} + \sum_{i=1}^{n} fGHG_{CO_{2},i,t}$$
(20)

where:

fGHG _{P,t}	is the rate of GHG emissions from the project area at monitoring event t , measured using chambers (t CO ₂ -e per unit of time);
fGHG _{CH4_} i,t	is the rate of CH ₄ emissions from the project area in stratum i at monitoring event t (t CO ₂ -e per unit of time);
<i>GWP</i> _{CH4}	is the global warming potential for CH_4 (per most recent version ACR Standard) (t CO_2 -e);
fGHG _{N2O_i,t}	is the rate of N ₂ O emissions from the project area in stratum i at monitoring event t (t CO ₂ -e per unit of time);
GWP_{N_2O}	is the global warming potential for N_2O (most recent version of ACR Standard) (t CO_2 -e);
fGHG _{CO2_} i,t	is the rate of project CO ₂ emissions from the project area in stratum i at monitoring event t (t CO ₂ -e per unit of time);
n	is the number of strata within the project boundary;
i	is the stratum within the project boundary; and
t	is the monitoring event.

Harvested Grain and Biomass

Introduction

The carbon in harvested grain and biomass represents an essential part of the net ecosystem exchange for baseline agricultural and rice project conditions when determined by eddy covariance (Equation 13). Harvested grain or biomass is determined by 1) collection of grain or biomass in representative plots within the stratum and 2) determination of the carbon and moisture content on the collected material using literature and laboratory analysis of the material and 3) estimation of total carbon removed in grain and/or biomass for the stratum. Alternatively, the Project Proponent may obtain information from the farmer about the weight of the harvested grain and/or biomass and use literature values and laboratory-determined values for the carbon and moisture content of the harvested grain and/or biomass to estimate Cgr_i , the carbon dioxide harvested or removed grain or biomass for the crop in stratum *i* (t CO₂-e) (Equation 21). The moisture content of the harvested material shall be determined at harvest. Methods described in Karlra²³ and McGeehan and Naylor²⁴ are applicable for determination of moisture content and carbon content.

Applicability Conditions

- 1. <u>Stratification</u>. The distribution of determination of Cgr_i shall be shown to adequately represent the hydrologic, water quality and soil conditions and land- and water-management practices for the stratum.
- 2. <u>Monitoring</u>. Annual estimates of Cgr_i are sufficient. For multiple harvests (such as for hay or grain crops), the annual estimate shall equal the sum of all harvests.
- 3. Monitoring must occur for baseline establishment and renewal. For project conditions, the monitoring frequency shall occur at least every 5 years over a period of one year.
- 4. The Project Proponent shall demonstrate using maps and photographs that yield plots are representative of the entire stratum.

Quality Control and Assurance Procedures

- 1. Where yield plots are used, plots shall be replicated three times within each stratum and the entire plot shall be harvested.
- 2. The average yield and standard deviation from the three replicate plots shall be used in uncertainty calculations in the uncertainty module (X-UNC).

Equations

For agricultural baseline conditions and rice project conditions, carbon removal in harvested biomass shall be estimated using the following equation²⁵:

²³ Karlra, Yash P. (ed.), 1998, Handbook of Reference Methods for Plant Analysis, CRC Press.

²⁴ McGeehan, S.L. and D.V. Naylor. 1988. Automated instrumental analysis of carbon and nitrogen in plant and soil samples. *Commun. Soil Sci. Plant Anal.* 19:493-505.

²⁵ E.g. Steven E. Hollinger, Carl J. Bernacchi, Tilden P. Meyers, 2005, Carbon budget of mature no-till ecosystem in North Central Region of the United States, Agricultural and Forest Meteorology 130 (2005) 59–69..

$$C_{gr} = W \times fC \times Y \tag{21}$$

where:

C_{gr}	is the carbon removal in harvested biomass (t CO_2 -e per unit	area);
W	is the moisture content expressed as a fraction;	
fC	is the fraction of carbon in the grain or biomass ²⁶ ; and	
Y	is the yield (t per unit area).	

The use of Equations 13 and 21 assumes that 100% of the harvested biomass is eventually consumed and oxidized to CO_2 and CH_4 which is released back into the atmosphere.

Aqueous Carbon Loads

Introduction

For baseline and project conditions, aqueous carbon loads (E_{aq} ,) represent part of the overall carbon budget as determined by eddy covariance (Equation 13). Aqueous carbon can enter and exit the project area to and from adjacent channels as dissolved and particulate organic carbon. The total organic carbon (TOC) concentration is equal to the sum of particulate and dissolved organic carbon. Loads are equal to the water flow times the concentration of total organic carbon in the water. The project Proponent shall utilize methods published in the peer-reviewed literature for determining concentrations, flow and loads in tidal^{27 28} and non-tidal²⁹ systems. For flow measurements, methods include manual flow and acoustic velocity meters. Methods for total dissolved organic carbon determination in drain-water samples are described in Deverel et al.³⁰

Specifically, for non-tidal managed wetlands, subsurface and surface drainage flow shall be measured and calculated continuously using traditional flow measurements using manually operated flow meters and tracking stage at a control device such as a weir with a water level recorder. Dissolved and particulate organic carbon concentrations shall be determined at intervals that adequately represent the temporal variability but not less than bimonthly. Alternatively, flow can be measured using

²⁶ Loomis, R.S., Conner, D.J., 1992. Crop Ecology: Productivity and Management in Agricultural Systems. Cambridge Univ. Press, New York, NY, 538 pp.

²⁷ Ganju NK, Schoellhamer DH, Bergamaschi ABA (2005) Suspended Sediment Fluxes in a Tidal Wetland: Measurement, Controlling Factors, and Error *Analysis Estuaries* **28**(6), 812–822.

²⁸Bergamaschi BA, Fleck JA, Downing BD, Boss E, Pellerin B, Ganju NK, Schoellhamer DH, Byington AA, Heim WA, Stephenson M, and Fujii R, (2011) Methyl mercury dynamics in a tidal wetland quantified using in situ optical measurements. *Limnol. Oceanogr.*, **56**(4), 2011, 1355–1371.

²⁹ E.g. Deverel, Steven J., David A. Leighton and Mark R. Finlay. Processes Affecting Agricultural Drainwater Quality and Organic Carbon Loads in California's Sacramento-San Joaquin Delta. San Francisco Estuary and Watershed Science. Vol. 5, Issue 2 [May 2007]. Article 2. http://repositories.cdlib.org/jmie/sfews/vol5iss2/art2.

³⁰ Deverel, Steven J., David A. Leighton and Mark R. Finlay. Processes Affecting Agricultural Drainwater Quality and Organic Carbon Loads in California's Sacramento-San Joaquin Delta. San Francisco Estuary and Watershed Science. Vol. 5, Issue 2 [May 2007]. Article 2. http://repositories.cdlib.org/jmie/sfews/vol5iss2/art2.

continuous recording acoustic Doppler technology. For tidal systems, a similar approach can be used except that flow is bidirectional depending on tidal influences.

Applicability Conditions

- 1. <u>Stratification</u>. The determination of E_{aq} , shall be shown to adequately represent the hydrologic, water quality and soil conditions and land- and water-management practices for the stratum.
- 2. <u>Monitoring</u>. Measurements shall adequately represent the temporal variability in concentrations and loads.
- 3. For non-tidal systems, the temporal variability is determined by hydrologic management and season variability. Monthly measurements are generally sufficient to characterize the temporal variability.
- 4. Tidal fluxes of dissolved and particulate organic carbon shall be estimated or measured at a time scale that allow determination of the net annual loss or gain of organic carbon to or from the wetland.

Quality Assurance

The uncertainty in manual flow measurements shall be determined as per guidance in Sauer and Meyer³¹ and incorporated in into the uncertainty equations in the uncertainty module (X-UNC). Uncertainty in acoustic velocity measurements shall be evaluated using information described in Laenen and Curtis³². Analytical uncertainty for dissolved organic carbon shall be determined using field duplicate and blank samples and laboratory QA/QC samples and shall be incorporated into the flow measurement uncertainty.

Equations

See Equation 14.

Subsidence Measurements

Introduction

Subsidence is caused by the oxidation of organic soils³³. As organic soils are drained for agricultural use and exposed to oxygen, they oxidize and disappear. Subsidence is estimated as the difference between elevations at two points in time. For the baseline scenario, subsidence measurements can be converted to carbon stock changes using methods described in Couwenberg and Hooijer³⁴ and here. Couwenberg and Hooijer described a simple approach to determining total net carbon loss from subsidence records.

http://www.escholarship.org/uc/item/7xd4x0xw.

³¹ Sauer, V.B. and R.W. Meyer. 1992. Determination of error in individual discharge measurements. Open-File Report 92-144. U.S. Geological Survey.

³² Laenan, Antoniua and Curtis, R.E., Accuracy of acoustic velocity metering systems for measurements of low velocity in open channels, US Geological Survey Water Resources Investigation Report 89-4090.

³³ Deverel S.J. and Leighton D.A., 2010, Historic, Recent, and Future Subsidence, Sacramento-San Joaquin Delta, California, USA. San Francisco Estuary and Watershed Science 8(2).

³⁴ Couwenberg J, Hooijer A (2013) Towards robust subsidence-based soil carbon emission factors for peat soils in south-east Asia, with special reference to oil palm plantations, *Mires and Peat*, **12**, 1–13.

If subsidence measurements are used, it is assumed that the soil carbon pool is decreasing via oxidation, and emissions are accounted for by ΔGHG using equation shown below. Where there are elevation measurements in organic or highly organic mineral soils, at two or more points in time, the difference in elevation and soil carbon density can be used to estimate historic baseline emissions by multiplying the elevation change by the soil carbon density. Soil carbon density is equal to the soil carbon content multiplied by the soil bulk density. Data for soil organic matter content for Delta and San Francisco Estuary soils is described in Callaway et al.³⁵ Deverel and Leighton³⁶ and Drexler et al.³⁷. Soil carbon content is equal to 50% of the soil organic matter content. Drexler et al. provided data for soil bulk density for eight Delta islands.

Applicability Conditions

- 1. Locations of measurements shall be determined by strata, known spatial variability and the required level of certainty as per guidance in the T-PLOT module. The determination of ΔGHG_{BSL} (Equation 22) shall be shown to adequately represent the hydrologic, water quality and soil conditions and land- and water-management practices for the stratum.
- 2. Project Proponents shall be conservative in estimating the depth of subsidence from elevation measurement differences by calculating the minimum possible difference between elevations measured at two points in time.
- 3. All elevation measurements for subsidence calculations shall be referenced to stable benchmarks.
- 4. Project Proponents shall insure and document the consistent use of vertical datums for elevations measured during different years.
- 5. Project Proponents shall use conservative values for soil organic carbon and bulk density values that result in conservative estimates for subsidence.

Quality Control and Quality Assurance Procedures

Uncertainty in subsidence estimates stem from 1) elevation measurements and 2) soil carbon and bulk density determinations. For elevation measurements, uncertainty is dependent on methods used which shall be documented and incorporated into uncertainty calculations in the uncertainty module (X-UNC). For example, Deverel and Leighton determined elevations at locations on Bacon Island in 2006 where elevations were measured by University of California researchers in 1978. The vertical closure error for the 1978 survey with traditional surveying equipment was 0.07 m. For the 2006 survey which utilized real time kinematic, static and fast-static Global Positioning System measurements vertical closure error was 0.002 m. Therefore, the conservatively estimated subsidence at any point along the survey route followed in 1978 and 2006 is equal to the elevation determined in 1978 minus the closure error minus

http://www.escholarship.org/uc/item/7xd4x0xw.

³⁵ Callaway, John C., Borgnis, Evyan L. Turner, R. Eugene & Milan, Charles S., 2012, Carbon Sequestration and Sediment Accretion in San Francisco Bay Tidal Wetlands, Estuaries and Coasts, (2012) 35:1163–1181.

³⁶ Deverel S.J. and Leighton D.A., 2010, Historic, Recent, and Future Subsidence, Sacramento-San Joaquin Delta, California, USA. San Francisco Estuary and Watershed Science 8(2).

³⁷ Drexler JZ, de Fontaine CS, Deverel SJ. 2009. The legacy of wetland drainage on the remaining peat in the Sacramento–San Joaquin Delta, California, USA.Wetlands 29:372–386.

the 2006 elevation plus the closure error. Table 18 shows an example calculation. Elevation errors in topographic-map elevations range from about 0.3 to 1 m.

Table 5. Example subsidence calculation for point 44027 on Figure 2 in Deverel and Leighton.

Year	Elevation (m)	Closure Error (m)	Depth of Subsidence (m)
1978	-3.98	0.07	
2006	-5.26	0.002	1.21 ((-3.98 – 0.07)- (-5.26+0.002)

Data presented in Drexler et al.³⁸ provide ranges of estimates for organic matter content and bulk density for eight Delta islands.

Equations

If measured by determining the depth of subsidence over a known period of time, ΔGHG_{BSL} represents the cumulative net emissions (t CO₂-e) due to the oxidation of organic soils as estimated by the depth of subsidence using the following equation

$$\Delta GHG_{BSL} = \frac{44}{12} \times \sum_{i=1}^{n} (S_i \times BD_i \times fC_i \times A_i)$$
(22)

where:

S	is the depth of land subsidence (m);
BD	is the dry bulk density of the peat (t m^{-3});
fC	is the fraction of carbon in the peat on a dry weight basis;
<u>44</u> 12	is the ratio of molecular weights of CO_2 to carbon (dimensionless);
A	is the area of the stratum (m ²);
i	refers to the stratum within the project boundary; and
n	is the number of strata within the project boundary.

Because the subsidence estimate represents the GHG emission due to organic carbon loss

$$\Delta GHG_{BSL} = \Delta C_{BSL} \tag{23}$$

³⁸ Drexler JZ, de Fontaine CS, Deverel SJ. 2009. The legacy of wetland drainage on the remaining peat in the Sacramento–San Joaquin Delta, California, USA.Wetlands 29:372–386.

(MM-W/R) (MODEL-W/R) (X-UNC) (TOOLS)

Soil Coring

Introduction

Carbon stock changes in the soil carbon pool in managed non-tidal wetlands and tidal wetlands can be measured in soil cores by determining the carbon accumulated above feldspar markers or sediment pins pounded into the ground to refusal³⁹ placed at the start of project activities. The material located above the feldspar marker or sediment pin/sediment interface shall be analyzed for total carbon or organic matter content and bulk density. Any compaction that occurs should be measured and accounted for. The change in carbon stocks in soil cores shall be determined by quantifying the carbon density above a marker horizon defined by a feldspar marker.

Feldspar markers should be placed at the start of the project activity. Feldspar marker horizons are prepared by spreading a thin aqueous slurry (~1 cm) layer of feldspar clay on the wetland⁴⁰ surface. Soil carbon content can be determined using elemental analysis using a CHN analyzer⁴¹ or estimated from the loss-on-ignition method⁴² (LOI). Results throughout the Sacramento-San Joaquin Delta and San Francisco Estuary^{43 44 45} demonstrate a statistically significant relation between soil carbon content and LOI. These regression relations yield similar results for determination of soil organic carbon from LOI and can be used to calculate the carbon content of the harvested cores on a mass carbon per mass of soil basis. Alternatively, a relationship can be established between loss on ignition of organic matter and organic carbon content by determining both and conducting simple regression analysis. Then the organic carbon content can be estimated using the cheaper/simpler analysis of LOI.

To estimate carbon density in mass per unit volume, multiply the carbon content times the bulk density. The bulk density shall be determined using methods reported in Calloway et al.⁴⁶ and Blake and Hartge⁴⁷.

Sediment Accretion in San Francisco Bay Tidal Wetlands, Estuaries and Coasts (2012) 35:1163–1181.

³⁹ US Geological Survey. 2012. Sediment pin standard operating procedures. Unpublished protocols. USGS, Western Ecological Research Center, San Francisco Bay Estuary Field Station, Vallejo, CA. http://www.tidalmarchmonitoring.org/ndf/USGS_WERC_Sediment_Pin_SOP.ndf

http://www.tidalmarshmonitoring.org/pdf/USGS-WERC-Sediment-Pin-SOP.pdf

⁴⁰ Cahoon, D. R. and R. E. Turner, 1989. Accretion and Canal Impacts in a Rapidly Subsiding Wetland. Feldspar marker horizon technique. Estuaries 12: 260-268.

⁴¹ Nelson, D.W. and Sommers, L.E., 1982, Total carbon, organic carbon, and organic matter *in* (Page, A.L., ed.) Methods of Soil Analysis, American Society of Agronomy, Madison, WI.

⁴² Ball,D.F. 1964. Loss-on-ignition as an estimate of organic matter and organic carbon in non-calcareous soils. Journal of Soil Science 15: 84–92. Craft, C.B., E.D. Seneca, and S.W. Broome. 1991. Loss on ignition and Kjeldahl digestion for estimating organic carbon and total nitrogen in estuarine marsh soils: calibration with dry combustion. Estuaries 14: 175–179.

⁴³ Drexler JZ, de Fontaine CS, Deverel SJ. 2009a. The legacy of wetland drainage on the peat resource in the Sacramento-San Joaquin Delta, California, USA. Wetlands 29:372–386.

⁴⁴ Callaway, J.C., Borgin, E.L., Turner, R. Eugene, Milan, Charles SI, 2012, Carbon Sequestration and Sediment Accretion in San Francisco Bay Tidal Wetlands, Estuaries and Coasts (2012) 35:1163–1181.

 ⁴⁵ Craft, C.B., E.D. Seneca, and S.W. Broome. 1991. Loss on ignition and Kjeldahl digestion for estimating organic carbon and total nitrogen in estuarine marsh soils: calibration with dry combustion. Estuaries 14: 175–179.
 ⁴⁶ John C. Callaway & Evyan L. Borgnis, R. Eugene Turner & Charles S. Milan, 2012, Carbon Sequestration and

⁴⁷ Blake, G.R. and Hartge, K.H., 1986, Bulk density in Klute, Arnold (ed). Methods of Soil Analysis, Physical and Mineralogical Methods, American Society of Agronomy, Madison, WI.

Specific steps for core collection:

Step 1. Collect soil core samples and measure the depth of the feldspar marker or measure the sediment accumulated at the sediment pin and collect a soil core sample to the depth of accumulated sediment. See quality assurance section below for discussion of compaction and compaction avoidance.

Step 2. Aggregate samples from plots as per guidance provided in the uncertainty module for estimating the number of samples and uncertainty.

Step 3. For bulk density analysis, a single core shall be collected next to the core collected for determination of soil carbon content. Bulk density shall be determined as per methodology described in Blake and Hartge. Soil samples need to be thoroughly dried until their weight no longer changes and then the weight of each section needs to be divided by the volume.

Step 4. The mass of carbon per unit volume is calculated by determining the product of the carbon concentration and bulk density (g/cm³).

Applicability Conditions

Locations of measurements shall be determined by strata, known spatial variability and the required level of certainty as outlined in the T-PLOT module. The determination of ΔC_p (Equation 24) shall be shown to adequately represent the hydrologic, water quality and soil conditions and land- and water-management practices for the stratum.

Quality Control and Quality Assurance Procedures

The primary quality control/quality considerations are related to 1) accurate depth of the core and 2) spatial variability in determinations of ΔC_p . Compaction during core collection is estimated by measuring the difference in elevation inside and outside of the coring tube to the nearest millimeter. Example coring devices include McAuley⁴⁸, Livingstone⁴⁹ or Hargis⁵⁰ coring devices that allow cores to be taken with minimal or no compaction. Strata and known spatial variability shall determine the number of samples and the required level of certainty as described in the T-PLOT tool.

If inorganic carbon is present in soil samples, there may be interference in the determination of soil organic carbon. Total inorganic carbon can be determined and subtracted from the organic carbon determination.

Equations

Where soil coring is used to estimate cumulative carbon stock changes in t CO₂-e,

⁴⁸ Bricker-Urso S, Nixon SW, Cochran JK, Hirschberg DJ, Hunt C (1989) Accretion Rates and Sediment Accumulation in Rhode Island Salt Marshes. *Estuaries* **12**, 300-317.

⁴⁹ Wright Jr HE (1991) Coring tips. Journal of Paleolimnology **6**:37–49.

⁵⁰ Hargis TG, Twilley RR (1994) Improved coring device for measuring soil bulk density in a Louisiana deltaic marsh. Journal of Sedimentary Research Section A: *Sedimentary Petrology and Processes* **64**, 681–683.

$$\Delta C_p = (\frac{1}{N} * \sum_{i=1}^{n} (D_i * CD_i))$$
(24)

where:

- *CD_i,* is the carbon density of the soil accumulated above a feldspar marker (product of the soil carbon content on a weight basis and soil bulk density);
- *i* is the stratum within the project boundary (1,2,3,...M); and
- *N* is the number of cores collected with stratum *i*.

In this case, CH₄ emissions are measured using chambers or eddy covariance as described above.

Methods used for inputs to biogeochemical models

The methods described in this section shall be used solely to determine inputs to biogeochemical models. The Project Proponents shall demonstrate that the estimated atmospheric GHG removal by above- and below-ground biomass is not additive to the determination of the overall carbon stock change calculation.

Above- and Below Ground Biomass and Litter Decomposition for Use in Biogeochemical Modeling Rates of carbon accumulation in above- and below-ground biomass can be measured using direct measurements (allometric determinations and harvesting) and indirect methods, which include use of remote sensing techniques. Litter decomposition can be estimated using traditional litterbags, isotopic analysis and modeling.

Estimating Above- and Below Ground Biomass Using Allometric and Destructive Methods

The mean carbon stock in aboveground and below-ground biomass per unit area is estimated based on field measurements of the wetland plants in fixed area plots using allometric equations and destructive methods such as those described in Miller and Fujii⁵¹ (Table 19). The number and size of plots shall ensure adequate representation of the area being measured by utilizing guidance provided in the module T-PLOTS. The allometric method can be used to estimate aboveground biomass by using equations that express aboveground biomass as a function of plant height and diameter. Miller and Fujii used extensive destructive biomass harvest to determine parameters in allometric equations for the

⁵¹ Miller, Robin L. and Fujii, Roger, 2010, Plant community, primary productivity, and environmental conditions following wetland re-establishment in the Sacramento-San Joaquin Delta, California, Wetlands Ecol Manage (2010) 18:1–16.

predominant species (*Typha and Schoenoplectus spp*) in managed non-tidal wetlands in the Sacramento-San Joaquin Delta. The following table provides the equations from Miller and Fujii.

Species	SI Unit	Equation
Schoenoplectus	Biomass weight in	$\log_{10} weight = (0.5028 * \ln height) + (0.3471 * \ln diameter) - 1.7654$
acutus	grams per square	$r^2 = 0.924$
	meter	
	meter	
Schoenoplectus	Biomass weight in	$\log_{10} weight = (0.7947 * \ln height) - 3.2177$
acutus	grams per square	$r^2 = 0.824$
	meter using only	
	height	
Typha. Species	Plant biomass weight	$\log_{10} weight = -2.188 + (0.601 * \ln height) + (0.2128 * \ln diameter)$
	in grams por square	$+(0.2721 * \ln leaf number) - 0.484$
	in grains per square	
	meter	$r^2 = 0.9$

Table 6. Allometric equations for above ground biomass estimates expressed in grams of biomass per square meter).

Miller and Fujii reported root biomass measurements and root:shoot ratios ranging from 0.6 ± 0.2 to 1.7 ± 0.4 for *Schoenoplectus acutus* and 0.7 ± 0.1 to 1.0 ± 0.3 for *Typha sp.* Values varied seasonally and with water depth. Average values for both species were not significantly different; 0.9 ± 0.1 for *Schoenoplectus acutus* and 0.8 ± 0.1 for *Typha sp.* For the purposes of this methodology for constructed wetland activities where these species are present, these values are appropriate for multiplication times the above-ground biomass weight. Destructive methods such as those described in Miller and Fujii can also be used to determine root biomass.

Estimating Above- and Below Ground Biomass Using Remote Sensing Methods

Spectral information from remotely sensed imagery can be used to estimate above-ground biomass. This spectral information can be used to not only estimate above-ground biomass but the fraction of photosynthetically active material driving photosynthesis as well as the timing and duration of the growing season.

Phenocam

Phenocams are digital cameras that are automated to record images of canopy cover throughout the year. These images can then be processed to calculate a greenness index (GI) which can be empirically related to above-ground leaf area index (LAI) based on field measurements where LAI is defined as half the total developed area of green leaves per unit ground surface area. LAI can be directly measured using destructive field sampling or measured using a LAI sensor such as the LAI-2200C Plant Canopy Analyzer (LI-COR, Lincoln, NE, USA)⁵². Measurements must be collected three times per month during the growing season. LAI can be used to estimate gross primary productivity for project conditions (managed and tidal wetlands and rice), which is an input to biogeochemical models.

⁵² Sonnentag, O., et al. (2011) Tracking the structural and functional development of a perennial pepperweed (Lepidium latifolium L.) infestation using a multi-year archive of webcam imagery and eddy covariance measurements. Agricultural and Forest Meteorology 151.

Satellite images

Satellite-derived LAI products give information across large spatial scales (e.g. 1km for MODIS) with fairly high temporal resolution (e.g. 8-16 days for MODIS). The drawbacks to this method include poor small-scale resolution associated with high uncertainty at the field scale as well as data gaps associated with cloud cover⁵³. Satellite-derived LAI products are therefore ideal for projects encompassing large spatial scales (multiple square kilometers) and may need to be supplemented with direct measurements.

Litter Decomposition

Litter decomposition represents a large term in the global carbon budget, playing a critical role in regulating soil carbon dynamics across multiple scales of space and time⁵⁴. To accurately predict litter carbon stock changes, litter decomposition rates (k) must be measured or estimated for project conditions. Litterbags are the most widely used method for direct k calculations and have been used and replicated around the world for decades⁵⁵ and can be used within this methodology. The analysis of natural abundances of ¹³C isotopes⁵⁶ as well as labeling experiments with isotopically enriched litter⁵⁷ are also effective ways to estimate litter carbon stock changes over time. Laboratory microcosm studies show large discrepancy in relation to field litterbag and isotopic studies and shall not be used. Modeled decomposition rates on the long-term inter-site decomposition experiment team (LIDET)⁵⁸ can be used to provide conservative estimates of decomposition.

Predicting root decomposition at wetland sites is greatly improved by estimating decomposition rates of wetland roots separately from all other litter. The LIDET databases can be used to generate conservative root decomposition estimates. The same methods shall be employed to estimate k values under baseline and project conditions. If models are used, they shall be constrained by main drivers of decomposition, such as geographic factors (latitude and altitude), climatic factors (temperature, precipitation, evapotranspiration) and litter quality (C:N ratios, lignin content) and calibrated using data for the project or demonstrably equivalent conditions.

⁵³ Garrigues, S., *et al.* (2008) Validation and intercomparison of global Leaf Area Index products derived from remote sensing data. *Journal of Geophysical Research: Biogeosciences* 113, G02028.

⁵⁴ Zhang D, Hui D, Luo Y, Zhou G (2008) Rates of litter decomposition in terrestrial ecosystems: global patterns and controlling factors. *Journal of plant ecology*, 2, 85-93.

⁵⁵ Olson JS (1963) Energy stores and the balance of producers and decomposers in ecological systems. Ecology 44:322–31.

⁵⁶ Silva LCR, Corrêa RS, Doane TA, Pereira EIP, Horwath WR. (2013) Unprecedented carbon accumulation in mined soils: the synergistic effect of resource input and plant species invasion *Ecological Applications* 23 (6), 1345-1356 2013.

 ⁵⁷ Qiao Y, Miao M, Silva LCR, Horwath WR (2014) Understory species regulate litter decomposition and accumulation of C and N in forest soils: A long-term dual-isotope experiment *Forest Ecology and Management*.
 ⁵⁸ Bonan GB, Hartman MD, Parton WJ, Wieder WR (2013) Evaluating litter decomposition in earth system models with long-term litterbag experiments: an example using the Community Land Model version 4 (CLM4). *Glob Chang Biol* **19**(3):957-74.

(MM-W/R) (MODEL-W/R) (X-UNC) (TOOLS)

29

(Model –W/R) Wetland Restoration and Rice Methodological Module-Biogeochemical Model Module

Scope

This module allows for the *ex-ante* and *ex-post* estimation of greenhouse gas (GHG) removals and emissions reductions for managed wetlands in the project scenario. For project conditions, this module uses a validated process-based biogeochemical model, the Peatland Ecosystem Photosynthesis, Respiration, and Methane Transport model (PEPRMT, pronounced "peppermint"), that can be used for *ex-ante* estimation of CO₂ and CH₄ exchange from wetlands in the Sacramento-San Joaquin Delta. This model has been calibrated and validated using a multi-year data set collected in a 14-acre mature restored wetland on Twitchell Island. Future updates to this model, including calibrations to restored wetlands of different ages (1-17 yr) and a rice paddy, will be made publically available (<u>https://github.com/pattyoikawa/PEPRMT.git</u>).

For baseline conditions, the SUBCALC model (Deverel and Leighton, 2010) may be used to estimate baseline CO₂ emissions. SUBCALC simulates microbial oxidation or agricultural organic soils using Michaelis–Menten kinetics. Parameters for the model Michaelis–Menten equations were developed from field data (Deverel and Rojstaczer, 1996). Inputs for the model are described in Deverel and Leighton and include soil organic matter content, average soil annual temperature at 30 cm, depth to groundwater, soil bulk density. We plan to integrate the SUBCALC and PEPRMT models for predicting both CO₂ and CH₄ from diverse land use types in the Delta.

Applicability Conditions and Methodological Requirements

The following conditions must be met for this module to be used:

- 1. For project areas that are converted to flooded conditions, separate model simulations must be run for baseline and project conditions.
- 2. The participating wetlands shall be in the Delta area of organic soils where the models have been successfully calibrated.
- 3. The model described here is applicable to fully vegetated wetlands or strata.
- 4. Wetlands or strata with open water require separate validation⁵⁹.
- 5. Net aqueous loss of carbon must be negligible or estimated using other methods (see Methods Module MM-W/R). Sites with significant import and/or export of dissolved forms of carbon (such as tidal wetlands) are not appropriate sites for employing the LUE-DAMM. For each model run, appropriate input parameter files must be available to the verifier.

⁵⁹ Conditions 3 and 4 represent different conditions that may occur in the same wetland or stratum due to hydrologic conditions or the stage of development. The model described in this module was developed for fully vegetated conditions.

Parameters

Parameter	SI Unit	Description
ΔC_{BSL}	t CO ₂ -e	Cumulative total of carbon stock changes and greenhouse gas
		emissions for the baseline scenario. This parameter feeds into
		Equation 1 in the Framework Module.
ΔC_{actual}	t CO ₂ -e	Cumulative total of carbon stock changes and greenhouse gas
		emissions for the project scenario. This parameter feeds into
		Equation 1 in the Framework Module.

Project Model Description

The PEPRMT model requires leaf area index (LAI), meteorological data, initial soil organic carbon content (SOC), and water table height. See Data and Parameters Monitored section for description and requirement for each input.

Model Calibration and Validation

In order to use this model in systems in which it has not been calibrated such as rice fields in the Sacramento Valley, it needs to be calibrated and validated using at least 2 years of semi-continuous ecosystem exchange data of CO_2 and CH_4 . Other model input variables will also need to be recorded during this time. Two years is the minimum in order for sufficient data for both parameterization and validation (recommended 70% data used for parameterization and 30% for validation). Model calibration and validation do not need to be conducted within project bounds but must be conducted in and documented for a similarly managed system with similar soil qualities and climate conditions.

Table 7. Project emissions sources i	included in t	the project	boundary
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Source	Gas
Net GHG emissions due to C	CO ₂ , CH ₄
uptake, ecosystem	
respiration and	
methanogenesis	

Quantification of Project Emissions and Carbon Stock Changes

Project emissions of CO₂ and CH₄ may be estimated using the PEPRMT model, which must be run separately for each wetland site, strata or cohort. Flux rates derived from the PEPRMT model, net ecosystem exchange of CO₂ (NEE; g CO₂ acre⁻¹ day⁻¹) and net ecosystem exchange of CH₄ (R_{CH4}; g CH₄ acre⁻¹ day⁻¹) will be used to derive annual sums of CO₂ and CH₄ for each project year and project site:

$$[CO_2]_{project,y,i} = \sum_{t=1} NEE_{project,t} * A \qquad (25)$$

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$$[CH_4]_{project,y,i} = \sum_{t=1}^{N} R_{CH_4 project,t} * A \qquad (26)$$

where:

[CO ₂]project,y,i	is the cumulative project net CO ₂ ecosystem exchange (<i>NEE</i>) from wetland stratum <i>i</i> over reporting time period which may vary from 0.5 to 2 years;
[CH ₄] _{project,y,i}	is the cumulative project net CH ₄ ecosystem exchange (R_{CH4}) from wetland stratum <i>i</i> over reporting time period which may vary from 0.5 to 2 years;
NEE _{project,t}	is the project net CO_2 ecosystem exchange flux rate at time <i>t</i> for wetland stratum <i>i</i> (g CO_2 acre ⁻¹ day ⁻¹);
R _{CH4project,t}	is the project net CH_4 ecosystem exchange flux rate at time <i>t</i> for wetland stratum <i>i</i> (g CH_4 acre ⁻¹ day ⁻¹); and
A	is the area in wetland stratum <i>i</i>

Project annual net GHG exchanges for each year and site are then used to calculate total project net emissions:

$$\Delta C_{actual} = \frac{44}{12} * [CO_2]_{project,y,i} + 25 * \frac{16}{12} * [CH_4]_{project,y,i}$$
(27)

where:

ΔC_{actual}	is the cumulative total of carbon stock changes and greenhouse gas emissions for the project scenario wetland site (t CO_2 -e);
[CO ₂]project,y,i	is the cumulative project net CO_2 ecosystem exchange (<i>NEE</i>) from wetland stratum <i>i</i> over reporting time period which may vary from 0.5 to 2 years;
[CH ₄] _{project,y,i}	is the cumulative project net CH ₄ ecosystem exchange (R_{CH4}) from wetland stratum <i>i</i> over reporting time period which may vary from 0.5 to 2 years;
44/12	is the ratio of molecular weight of CO_2 to carbon (dimensionless); and
16/12	is the ratio of molecular weight of CH4 to carbon (dimensionless).

The current *ACR Standard* provides reference for the Global Warming Potential for methane on a 100-yr timescale.

Project Model description: The Peatland Ecosystem Photosynthesis, Respiration, and Methane Transport model (PEPRMT)

I. CO₂ ecosystem PEPRMT model

In order to predict net ecosystem exchange of CO_2 (NEE) both gross primary productivity (GPP) and ecosystem respiration (R_{eco}) need to be simulated:

$$NEE = GPP + R_{eco} \tag{28}$$

To predict GPP, we employ a simple and widely-used light use efficiency model called the LUE model (Monteith, 1977):

$$GPP = PAR * \varepsilon * fPAR(LAI) * f(T)$$
(29)

where GPP is a function of available photosynthetically active radiation (*PAR*), plant light use efficiency (ε), the fraction of PAR absorbed by canopy (*fPAR*) which is a function of leaf area index (*LAI*), and a temperature function (*f(T)*). The light use efficiency and temperature function are calibrated to each ecosystem, as these vary among plant species (Yuan *et al.*, 2007). The temperature function assumes photosynthesis increases exponentially with temperature until it reaches an optimum (e.g. 25°C), above which photosynthesis is inhibited:

$$f(T_k) = 1 * \left(\frac{H_d(T_k - T_{opt}))}{H_d - H_a(1 - exp\left(\frac{H_d(T_k - T_{opt})}{T_k * R * T_{opt}}\right)} \right)$$
(30)

where *R* is the universal gas constant, T_k is air temperature, H_a is the rate of exponential increase below the optimum temperature, and H_d is the rate of decrease above the optimum temperature (Medlyn *et al.*, 2002). From these equations, photosynthetic rates are computed every 30 min and up-scaled to the ecosystem using LAI.

Ecosystem respiration (R_{eco}) is the total CO₂ respired by both plants and soil. In order to predict R_{eco} we employ a simple respiration model based on enzyme kinetics which was adapted from the Dual Arrhenius Michaelis-Menten kinetics (DAMM) model (Davidson *et al.*, 2012). This model assumes R_{eco} is a function of the size and availability of 2 soil C pools, temperature, and water table height (WT). The 2 soil carbon pools are regulated by initial soil carbon conditions (i.e. soil organic carbon (SOC)) and recently-fixed photosynthetic C, which is predicted using GPP. According to enzyme kinetics, respiration increases exponentially with temperature. Water table and soil moisture influence the availability of oxygen in the soil, an important substrate for aerobic respiration. Specifically, R_{eco} is predicted using an Arrhenius equation paired with Michaelis-Menten equations to address substrate availability of 2 C pools:

$$R_{eco} = \left(\frac{Vmax_{SOC} * [C_{SOC}]}{kM_{SOC} + [C_{SOC}]} + \frac{Vmax_{labile} * [C_{labile}]}{kM_{labile} + [C_{labile}]}\right) * f(WT)$$
(31)

where R_{eco} is the total respiration rate for the given ecosystem (µmol CO₂ m⁻² s⁻¹), V_{max} (µmol CO₂ m⁻² s⁻¹) is the maximum rate of enzyme kinetics for the respective C pools when substrate concentrations are not limiting (where labile refers to recently-fixed photosynthetic C and soil organic carbon (SOC) refers

to older more recalcitrant forms of C), *C* is the soil C content for the respective C pools (μ mol C m⁻²), and *kM* is the half-saturation concentration for the respective substrates (μ mol C m⁻²). Under flooded conditions, soil respiration is inhibited due to depleted O₂. Soil CO₂ emission rates under anaerobic conditions have been previously reported to decrease by 32-65%⁶⁰ due to the use of alternative electron acceptors, and were recently reported to be reduced by 50% in a Delta rangeland site (McNicol & Silver, 2014). Therefore the water table function (*f* (*WT*)) describes elevated rates of respiration when the water table falls below the soil surface due to introduction of O₂ to the soil.

C pool sizes are dynamic. For example, both pools are reduced in response to respiration rates. The SOC pool is enhanced at the end of the year when vegetation senesces and contributes to the SOC pool, estimated as a function of LAI. The labile pool is a function of *GPP* (explained above). Initial SOC conditions for the simulated region is another driver for model simulation and must be sampled at the beginning of the project (5-10 soil profile samples to assess average SOC in the top 1m of soil; see Tables 21-23 for complete list of drivers, parameters and state variables).

Following the Arrhenius function, V_{max_x} is the maximum rate of enzyme reaction for each soil C pool (i.e. SOC and labile soil C):

$$V_{max} = a_x * e^{-Eax/RT} \tag{32}$$

where V_{max_x} is predicted using the pre-exponential factor (a_x) , the activation energy of the enzymatic reaction with the substrate (Ea_x) , air temperature (T) and the universal gas constant (R).

II. CH₄ ecosystem PEPRMT model

In order to predict net CH₄ emissions, both methane oxidation and production need to be simulated. Again, we employ a simple model based on enzyme kinetics where CH₄ production is a function of the size and availability of two soil C pools, temperature, and water table height, and CH₄ oxidation is a function of the availability of CH₄, temperature, and water table height. Both processes are predicted to increase exponentially with temperature. However, high water table conditions enhance CH₄ production and limit oxidation and low water table heights inhibit CH₄ production and increase oxidation. Two transport pathways are also modeled, plant–mediated CH₄ transport and hydrodynamic CH₄ flux. Both of these transport pathways are dependent on water table height and concentration gradients of CH₄ between the water and atmosphere. Plant-mediated transport is also a function of GPP.

The biogeochemical model for CH_4 production and oxidation is based on the DAMM model foundation. Similarly to the R_{eco} DAMM model, CH_4 production is predicted using an Arrhenius equation paired with Michaelis-Menten equations estimating the concentration of two C substrates at the enzyme reaction site:

$$R_{CH4} = \frac{V_{max_{labile}} * [C_{labile}]}{kM_{labile} + [C_{labile}]} * \frac{V_{max_{SOC}} * [C_{SOC}]}{kM_{SOC} + [C_{SOC}]} * f(WT)$$
(33)

To account for the inhibition of CH_4 production by the presence of O_2 , an O_2 effect parameter is applied when the water table falls below the soil surface. Previous research has indicated that CH_4 production

⁶⁰ Wright AL, Reddy KR (2001) Heterotrophic microbial activity in northern Everglades wetland soils, *Soil Sci Soc Am J*, 65:1856–1864.

rates can take multiple days to recover following re-saturation, due to the slow recharge of alternative electron acceptors (Kettunen *et al.*, 1999, Moore & Dalva, 1993). A previous analysis at the West Pond wetland confirmed that lowering the water table can have sustained negative effects on CH_4 emission, lasting up to 20 days (Sturtevant *et al.*, 2015). We added a lag effect into the model, where CH_4 production is inhibited for 20 days following a drop in the water table.

Similarly, CH₄ oxidation follows the DAMM model foundation, where there is only 1 substrate pool: CH₄:

$$O_{CH4} = \frac{Vmax_{CH4} * [CH_4]}{kM_{CH4} + [CH_4]} * f(WT)$$
(34)

To account for the inhibition of CH_4 oxidation when the water table is above the soil surface, a water table function (f(WT)) is applied when the water table is above the soil surface.

Hydrodynamic flux is predicted using the Poindexter model, which was parameterized and validated at the same mature wetland site as the model described here (Poindexter *et al. submitted*). This predicts transfer of CH_4 stored in the water directly to the atmosphere given the concentration gradient between CH_4 in water and CH_4 in the atmosphere as well as a gas transfer velocity:

$$F_{hydro} = k_{hydro} * \left([CH4_{water}] - [CH4_{surface}] \right)$$
(35)

Where k_{hydro} is the gas transfer velocity through the water (0.04 m d⁻¹). Concentrations of CH₄ in the water or soil ([*CH*_{4water}]; µmol m⁻³) are modeled based on production and oxidation rates of CH₄. After accounting for methane solubility in water, dissolved concentrations of methane at the surface ([*CH*_{4surface}]; µmol m⁻³) are so small they are assumed to be zero.

Plant-mediated flux is predicted following the Dynamic Land Ecosystem Model (DLEM) (Tian *et al.*, 2010). This predicts plant-mediated transport of CH_4 given the concentration gradient between CH_4 in water and CH_4 in the atmosphere as well as plant transport efficiency and plant activity:

$$F_{plant} = \left(k_{plant} * \left([CH_{4_{water}}] - [CH_{4_{atm}}]\right) * \frac{GPP}{GPP_{max}}\right) * V_{oxi}$$
(36)

where k_{plant} is the gas transfer velocity through plants, assumed to be constant (0.24 m d⁻¹) (Kettunen, 2003). Concentrations of CH₄ in the soil and water ([CH_{4water}]; µmol m⁻³) are modeled based on production and oxidation rates of CH₄. Again, after accounting for methane solubility in water, dissolved concentrations of methane in the atmosphere ([CH_{4atm}]; µmol m⁻³) are so small they are assumed to be zero. Plant activity is assessed using GPP, where the most plant transport is expected to occur when GPP is at its highest point. Finally, a fraction of CH₄ transported through plants is assumed to be oxidized at a constant rate (V_{oxi} =0.35) (van der Nat & Middelburg, 1998b).



Figure 2. Conceptual diagram of PEPRMT model. Model inputs and drivers (air temperature (T_{air}), absorbed photosynthetically active radiation (APAR), water table height (WT), labile soil C, and soil organic carbon (SOC)) are shown in white boxes; model outputs are shown in grey boxes. Processes and pools modeled within PEPRMT are shown in pink and orange boxes, respectively.



Figure 3. (a) PEPRMT modeled and observed net ecosystem exchange of CO_2 (NEE) from July 2012 to December 2014 at West Pond wetland. Data to the left of the black vertical line were used in model parameterization and data to the right were used in model validation. (b) Data model agreement was high during the parameterization period (param) (slope=1, intercept=0.26; r2 = 0.92; RMSE = 0.85) and during the validation period (valid) (slope=1, intercept=0.13; r2 = 0.90; RMSE = 0.86). (c) Similar integrated observed and modeled NEE fluxes were observed during the validation period (observed: -290 ± 134g C-CO2 m-2 yr-1; modeled: -329.5 ± 105 g C-CO2 m-2 yr-1) as well as across the entire observation period (observed: -1220.6 ± 336g C-CO2 m-2 yr-1; modeled: -1107.0 ± 257 g C-CO2 m-2 yr-1). Errors are 90% confidence intervals. Observed error is the sum of random and gap-filling errors. Model error is calculated based on variance across accepted posterior model parameters.

Approximately 60% of observed data were used to parameterize the model (July 2012–December 2013), and 40% were used for model validation (January 2014–December 2014). PEPRMT model simulations explained 90% of the variation in observed CO₂ fluxes. Observed and modeled cumulative CO₂ budgets for the validation period were similar (observed: -290 ± 134g C-CO₂ m⁻² yr⁻¹; modeled: -329.5 ± 105 g C-CO₂ m⁻² yr⁻¹).



Figure 4. (a) PEPRMT modeled and observed ecosystem exchange of CH₄ in West Pond wetland. Data to the left of the black vertical line were used in model parameterization and data to the right were used in model validation. (b) Data-model agreement was high during the parameterization period (param) (slope = 0.76, intercept = 31; $r^2 = 0.60$; RMSE = 48.6) and during the validation period (valid) (slope = 0.7, intercept = 33; $r^2 = 0.67$; RMSE = 57.2). (c) Similar integrated observed and modeled CH₄ fluxes were observed during the parameterization period (observed: 47.9 ± 6 g C- CH₄ m⁻²; modeled: 41.0 ± 3.0 g C- CH₄ m⁻²) and validation period (observed: 40.3 ± 4.5 g C-CH₄ m⁻² yr⁻¹). Across the entire observation period budgets were similar (observed:

 88.2 ± 10.5 g C- CH₄ m⁻²; modeled: 81.4 ± 6.0 g C-CH₄ m⁻²). Errors are 90% confidence intervals. Observed error is the sum of random and gap-filling errors. Model error is calculated based variance across accepted posterior model parameters.

PEPRMT model simulations explained 65% of the variation in observed CH₄ fluxes. Observed and modeled cumulative CH₄ budgets for the validation period were very similar (observed: 40.3 ± 4.5 g C-CH₄ m⁻² yr⁻¹; modeled: 40.4 ± 2.8 g C- CH₄ m⁻² yr⁻¹).

Data and Parameters Monitored

Data Unit / Parameter	Meteorological data
Description	Air temperature and in-coming radiation
Units	Degree Celsius and μ mol radiation m ⁻² s ⁻¹
Data source	California Irrigation Management Information
	System (CIMIS) website
	(http://www.cimis.water.ca.gov/cimis/data.jsp)
Description of measurement methods and	
procedures to be applied	
Frequency of monitoring/recording	30 min
QA/QC procedures	
Verification requirements	
Comments	

Data Unit / Parameter	Initial soil organic carbon
Description	Amount of existing soil organic carbon at
	beginning of project
Units	g C m ⁻³ soil
Data source	Soil survey data (NRCS SSURGO) or direct sampling (5-10 soil profile samples averaged across top 1m soil; replicate spatially as needed)
Description of measurement methods and procedures to be applied	If data from NRCS SSURGO is used, the uncertainty in the spatial resolution of soils properties (including soil organic matter) must be accounted for in model inputs.
Frequency of monitoring/recording	Once at beginning of project
QA/QC procedures	
Verification requirements	
Comments	

Data Unit / Parameter

Water table height

Description	Distance from surface of soil to water table— for project conditions
Units	cm
Data source	Direct or automated measurement
Description of measurement methods and procedures to be applied	Measure by hand distance of water height to soil surface or install pressure transducer to continuously monitor water table height (such as Campbell Scientific CS451-L)
Frequency of monitoring/recording	Daily-weekly
QA/QC procedures	
Verification requirements	
Comments	

Data Unit / Parameter	Leaf area index
Description	One-sided green leaf area per ground surface
	area
Units	m^2 leaf area m^{-2} ground area
Data source	Destructive field sampling, LAI sensor (e.g.
	LAI-2200C Plant Canopy Analyzer), or
	remote sensing
Description of measurement methods and	Destructive sampling: remove all leaves in a
procedures to be applied	known surface area (e.g.40cm x 40cm),
	measure leaf area of all removed leaves.
	Repeat across landscape (ideally 5
	measurements per plant cover type).
	LAI sensor: collect 10 measurements along a
	transect through each plant cover type
	<u>Remote sensing</u> : Phenocams, or digital
	cameras that are automated to record images
	of canopy cover throughout the year, can be
	used to calculate a greenness index (GI)
	which can be empirically related to LAI based
	on field measurements (Richardson <i>et al.</i> ,
	2009, Kyu <i>et al.</i> , 2012, Sonnentag <i>et al.</i> , 2011). Other former of numeric consists may
	2011). Other forms of remote sensing may
	also be available such as satellite inlages
Fraguency of manitoring/recording	Measurements must be collected frequently
Frequency of monitoring/recording	during the growing season (2x per month):
	monthly measurements during the non-
	growing seasons are also required
0A/0C procedures	See Methods Module(MM-W/R)
Varification requirements	
Comments	
Comments	

Parameters, state variables, and driver variables	Description	Value
Parameters		
ε	Light use efficiency (g C MJ ⁻¹)	0.94
Ha	Activation energy for photosynthesis (kJ mol ⁻¹)	21.5
Ha	Inhibition of photosynthesis at high temperatures (kJ mol ⁻¹)	110
R	Universal gas constant	0.00831
Topt	Optimum temp for photosynthesis	25°C
State variables		
NEE	Net ecosystem exchange CO_2 (µmol m ⁻² s ⁻¹)	
GPP	Gross ecosystem primary productivity (µmol m ⁻² s ⁻¹)	
Driver variables		
Air temperature	°C	
PAR	Photosynthetically active radiation (μ mol m ⁻² s ⁻¹)	
LAI	Leaf area index	
Table 9. Respiration PEPRMT model para	meters, descriptions and values	
Parameters, state variables, and driver variables	Description	Value
Parameters		
kM _{labile}	Michaelis-Menten constant for labile C (g C cm ⁻³ soil)	1.7*10 ⁻⁶
kMsoc	Michaelis-Menten constant for SOC (g C cm ⁻³ soil)	6.3*10 ⁻⁶
Ø.labile	Pre-exponential factor for labile C (µmol C cm ⁻³ soil s ⁻¹)	2

<i>a</i> soc		
	Pre-exponential factor 2 for SOC (umol C cm^{-3}	
	$roi sole (\mu more em$	
E ma a m	Activation anarray for 18	
LU labile	labile C (kJ mol ⁻¹)	
Easoc	Activation energy for 17.8	
	SOC (kJ mol ⁻¹)	
Csoc	Initial SOC pool (mol C <i>measure</i>	d
	m ⁻³)	
State variables		
Reco	Ecosystem respiration	
	$(\text{umol } \text{m}^{-2} \text{ s}^{-1})$	
Csoc	SOC pool	
Driver variables		
Air Temp	°C	
PAR	Photosynthetically active	
	radiation (umol $m^{-2} s^{-1}$)	
WT	Water table height	
GPP	Gross ecosystem primary	
011	productivity (umol m^{-2} s ⁻	
Table 10. CH₄ PEPERMT model parame	eters, descriptions and values	
	and the second	
Parameters, state variables,	Description	Value
Parameters, state variables, and driver variables	Description	Value
Parameters, state variables, and driver variables	Description	Value
Parameters, state variables, and driver variables Parameters	Description	Value
Parameters, state variables, and driver variables Parameters <i>kM</i> _{labile}	Description Michaelis-Menten constant for labile	Value 2.3*10 ⁻⁵
Parameters, state variables, and driver variables Parameters kM _{labile}	Description Michaelis-Menten constant for labile C (g C cm ⁻³ soil)	Value 2.3*10 ⁻⁵
Parameters, state variables, and driver variables Parameters <i>kM</i> _{labile} <i>kM</i> _{soc}	Description Michaelis-Menten constant for labile C (g C cm ⁻³ soil) Michaelis-Menten constant for SOC	Value 2.3*10 ⁻⁵ 1.7*10 ⁻⁵
Parameters, state variables, and driver variables Parameters kMlabile kMsoc	Description Michaelis-Menten constant for labile C (g C cm ⁻³ soil) Michaelis-Menten constant for SOC (g C cm ⁻³ soil)	Value 2.3*10 ⁻⁵ 1.7*10 ⁻⁵
Parameters, state variables, and driver variables Parameters kM _{labile} kM _{soc} kM _{cH4}	Description Michaelis-Menten constant for labile C (g C cm ⁻³ soil) Michaelis-Menten constant for SOC (g C cm ⁻³ soil) Michaelis-Menten constant for CH ₄	Value 2.3*10 ⁻⁵ 1.7*10 ⁻⁵ 2.3*10 ⁻⁵
Parameters, state variables, and driver variables Parameters kMlabile kMsoc kMcH4	Description Michaelis-Menten constant for labile C (g C cm ⁻³ soil) Michaelis-Menten constant for SOC (g C cm ⁻³ soil) Michaelis-Menten constant for CH ₄ oxidation (g C cm ⁻³ soil)	Value 2.3*10 ⁻⁵ 1.7*10 ⁻⁵ 2.3*10 ⁻⁵
Parameters, state variables, and driver variables Parameters kMlabile kMsoc kMcH4 alabile	Description Michaelis-Menten constant for labile C (g C cm ⁻³ soil) Michaelis-Menten constant for SOC (g C cm ⁻³ soil) Michaelis-Menten constant for CH ₄ oxidation (g C cm ⁻³ soil) Pre-exponential factor for labile C	Value 2.3*10 ⁻⁵ 1.7*10 ⁻⁵ 2.3*10 ⁻⁵ 6*10 ⁸
Parameters, state variables, and driver variables Parameters kMtabile kMsoc kMcH4 αtabile	Description Michaelis-Menten constant for labile C (g C cm ⁻³ soil) Michaelis-Menten constant for SOC (g C cm ⁻³ soil) Michaelis-Menten constant for CH ₄ oxidation (g C cm ⁻³ soil) Pre-exponential factor for labile C (μmol C cm ⁻³ soil s ⁻¹)	Value 2.3*10 ⁻⁵ 1.7*10 ⁻⁵ 2.3*10 ⁻⁵ 6*10 ⁸
Parameters, state variables, and driver variables Parameters kM _{labile} kMsoc kMcH4 alabile asoc	Description Michaelis-Menten constant for labile C (g C cm ⁻³ soil) Michaelis-Menten constant for SOC (g C cm ⁻³ soil) Michaelis-Menten constant for CH ₄ oxidation (g C cm ⁻³ soil) Pre-exponential factor for labile C (μmol C cm ⁻³ soil s ⁻¹) Pre-exponential factor for SOC	Value 2.3*10 ⁻⁵ 1.7*10 ⁻⁵ 2.3*10 ⁻⁵ 6*10 ⁸ 6*10 ⁷
Parameters, state variables, and driver variables Parameters kMlabile kMsoc kMcH4 αlabile αsoc	Description Michaelis-Menten constant for labile C (g C cm ⁻³ soil) Michaelis-Menten constant for SOC (g C cm ⁻³ soil) Michaelis-Menten constant for CH ₄ oxidation (g C cm ⁻³ soil) Pre-exponential factor for labile C (μ mol C cm ⁻³ soil s ⁻¹) Pre-exponential factor for SOC (μ mol C cm ⁻³ soil s ⁻¹)	Value 2.3*10 ⁻⁵ 1.7*10 ⁻⁵ 2.3*10 ⁻⁵ 6*10 ⁸ 6*10 ⁷
Parameters, state variables, and driver variables Parameters kM _{labile} kMsoc kMcH4 a _{labile} asoc acH4	Description Michaelis-Menten constant for labile C (g C cm ⁻³ soil) Michaelis-Menten constant for SOC (g C cm ⁻³ soil) Michaelis-Menten constant for CH ₄ oxidation (g C cm ⁻³ soil) Pre-exponential factor for labile C (μmol C cm ⁻³ soil s ⁻¹) Pre-exponential factor for SOC (μmol C cm ⁻³ soil s ⁻¹) Pre-exponential factor for CH ₄	Value 2.3*10 ⁻⁵ 1.7*10 ⁻⁵ 2.3*10 ⁻⁵ 6*10 ⁸ 6*10 ⁷ 6*10 ⁷
Parameters, state variables, and driver variables Parameters kM_{labile} kM_{soc} kM_{CH4} α_{labile} α_{SOC} a_{CH4}	Description Michaelis-Menten constant for labile C (g C cm ⁻³ soil) Michaelis-Menten constant for SOC (g C cm ⁻³ soil) Michaelis-Menten constant for CH ₄ oxidation (g C cm ⁻³ soil) Pre-exponential factor for labile C (μ mol C cm ⁻³ soil s ⁻¹) Pre-exponential factor for SOC (μ mol C cm ⁻³ soil s ⁻¹) Pre-exponential factor for CH ₄ oxidation (μ mol C cm ⁻³ soil s ⁻¹)	Value 2.3*10 ⁻⁵ 1.7*10 ⁻⁵ 2.3*10 ⁻⁵ 6*10 ⁸ 6*10 ⁷ 6*10 ⁷
Parameters, state variables, and driver variables Parameters kMlabile kMsoc kMcH4 alabile asoc aCH4 Ealabile	DescriptionMichaelis-Menten constant for labile C (g C cm ⁻³ soil)Michaelis-Menten constant for SOC (g C cm ⁻³ soil)Michaelis-Menten constant for CH4 oxidation (g C cm ⁻³ soil)Pre-exponential factor for labile C (µmol C cm ⁻³ soil s ⁻¹)Pre-exponential factor for SOC (µmol C cm ⁻³ soil s ⁻¹)Pre-exponential factor for CH4 oxidation (µmol C cm ⁻³ soil s ⁻¹)Pre-exponential factor for CH4 oxidation (µmol C cm ⁻³ soil s ⁻¹)Pre-exponential factor for CH4 oxidation (µmol C cm ⁻³ soil s ⁻¹)	Value 2.3*10 ⁻⁵ 1.7*10 ⁻⁵ 2.3*10 ⁻⁵ 6*10 ⁸ 6*10 ⁷ 6*10 ⁷ 71.1
Parameters, state variables, and driver variables Parameters kMtabile kMsoc kMcH4 alabile asoc acH4 Ealabile	DescriptionMichaelis-Menten constant for labile C (g C cm ⁻³ soil)Michaelis-Menten constant for SOC (g C cm ⁻³ soil)Michaelis-Menten constant for CH4 oxidation (g C cm ⁻³ soil)Pre-exponential factor for labile C (µmol C cm ⁻³ soil s ⁻¹)Pre-exponential factor for SOC (µmol C cm ⁻³ soil s ⁻¹)Pre-exponential factor for CH4 oxidation (µmol C cm ⁻³ soil s ⁻¹)Pre-exponential factor for CH4 oxidation (µmol C cm ⁻³ soil s ⁻¹)Activation energy for labile C (kJ mol ⁻¹)	Value 2.3*10 ⁻⁵ 1.7*10 ⁻⁵ 2.3*10 ⁻⁵ 6*10 ⁸ 6*10 ⁷ 6*10 ⁷ 71.1

Easoc	Activation energy for SOC (kJ mol ⁻¹)	67.1
Ea _{CH4}	Activation energy for CH ₄ oxidation	75.4
	(kJ mol ⁻¹)	
Csoc	Initial SOC pool (mol C m ⁻³)	measured
<i>k</i> _{plant}	Gas transfer velocity through plants	0.24 m d^{-1}
	(Kettunen et al. 2003)	
Voxi	Fraction of CH ₄ oxidized during plant	0.35
	transport	
<i>k</i> _{hydro}	Gas transfer velocity through water	0.04 m d^{-1}
	(Poindexter et al. submitted)	
State variables		
<i>RCH</i> ⁴	CH ₄ production (μ mol m ⁻² d ⁻¹)	
Осн4	CH ₄ oxidation (μ mol m ⁻² d ⁻¹)	
NCH4	Net CH ₄ emission (μ mol m ⁻² d ⁻¹)	
Ссн4	Soil CH ₄ pool	
Driver variables		
Air Temp	°C	
PAR	Photosynthetically active radiation	
	$(\mu \text{mol } \text{m}^{-2} \text{ s}^{-1})$	
WT	Water table height	
GPP	Gross ecosystem primary	
	productivity (µmol m ⁻² s ⁻¹)	

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Tian H, Xu X, Liu M, Ren W, Zhang C, Chen G, Lu C (2010) Spatial and temporal patterns of CH4 and N2O fluxes in terrestrial ecosystems of North America during 1979–2008: application of a global biogeochemistry model. Biogeosciences, 7, 2673-2694.

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Yuan W, Liu S, Zhou G et al. (2007) Deriving a light use efficiency model from eddy covariance flux data for predicting daily gross primary production across biomes. Agricultural and Forest Meteorology, 143, 189-207.

(EFFC –W/R) Wetland Restoration and Rice Methodological Module-Estimation of Emissions from Fossil Fuel Combustion

Project proponents will employ the currently approved method module for estimating GHG emissions fossil fuel combustion approved by ACR:

http://americancarbonregistry.org/carbon-accounting/standards-methodologies/restorationof-degraded-deltaic-wetlands-of-the-mississippi-delta/e-ffc.pdf

(MM-W/R) (MODEL-W/R) (X-UNC) (TOOLS)

Tools

(X-UNC) Methodological Module Tool for estimation of uncertainty for wetland construction and restoration and rice cultivation in the Sacramento-San Joaquin Delta and San Francisco Estuary

SCOPE, APPLICABILITY AND PARAMETERS

Scope

This module provides guidance for calculating uncertainty for estimation of emissions and GHG removals from wetland construction and restoration activities and rice cultivation activities implemented in the Sacramento-San Joaquin Delta and San Francisco Estuary where water quality ranges from fresh to saline conditions.

Applicability

This module is mandatory and provides guidance for the calculation of the following sources of uncertainty:

- Baseline and project emissions
- Baseline and project changes in soil carbon stocks

Where an uncertainty value is not known or cannot be accurately calculated, a Project Proponents shall justify that it is using an indisputably conservative value for carbon stock changes or emissions and an uncertainty of 0% may be used for this component.

Parameters

This module provides procedures to determine the following parameters:

Parameter	Description
UNC	Total (project and baseline) uncertainty (%)
Uncertainty _{BSL,SS,i}	Percentage uncertainty of the combined carbon stocks and greenhouse gas
	sources for the uncertainty baseline case in stratum i
Uncertainty _{P,SS,i}	Percentage uncertainty of the combined carbon stocks and greenhouse gas
	sources for the project scenario case in stratum i

Either as default values given in IPCC Guidelines for greenhouse gas (GHG) inventories⁶¹ good practice for land use⁶², expert judgment⁶³, or estimates based on sound sampling design and statistical analysis shall provide the basis for uncertainty calculations. Uncertainties arising from the measurement and monitoring of carbon pools and the changes in carbon pools shall always be quantified. Indisputably conservative estimates can also be used instead of uncertainties in which case the uncertainty is assumed to be zero. However, this section provides a procedure to combine uncertainty information

⁶¹ Eggleston S, Buendia L, Miwa K, Ngara T, Tanabe K (2006) IPCC Guidelines for National Greenhouse Gas Inventories.

⁶² Penman J, Gytarsky M, Hiraishi T, Krug T, Kruger D, Pipatti R, Buendia L, et al. (2003) IPCC Good Practice Guidance for Land Use, Land-Use Change and Forestry.

⁶³ Justification should be supplied for all values and parameters measured or derived from expert judgment.

and conservative estimates resulting in an overall project scenario uncertainty.

To calculate total project uncertainty the following equation shall be applied:

$$\text{Fotal (Project and Baseline) } UNC = \sqrt{UNC_{BSL}^2 + UNC_P^2}$$
(37)

Where:

UNC is the total (project and baseline) uncertainty (%);

 $\mathsf{UNC}_{\mathsf{BSL}}$ is the baseline uncertainty (%); and

UNC_P is the project uncertainty (%).

The allowable uncertainty under this methodology is $\pm 10\%$ of the mean carbon stock change at the 90% confidence level. Where this precision level is met, no deduction shall result for uncertainty. Where uncertainty exceeds 10% of the mean carbon stock change, the deduction shall be equal to the amount that the uncertainty exceeds the allowable level, as indicated in the Framework Module (WR-MF).

ESTIMATION OF BASELINE UNCERTAINTY

It is important that the process of project planning consider uncertainty. *A priori* estimations of statistical power⁶⁴ can be used to ensure proper spatiotemporal replication⁶⁵ and determine procedures, such as stratification and allocation of resources to allow the number of measurement plots to reduce uncertainty. It is good practice to consider uncertainty at an early stage to identify the data sources with the highest risk to allow the opportunity to conduct further work to improve representativeness and optimize project practices over time. Estimation of uncertainty for pools and emissions sources for each measurement pool requires calculation of both the mean and the 90% confidence interval. In all cases, uncertainty should be expressed at the 90% confidence interval as a percentage of the mean.

The uncertainty in the baseline scenario is defined as the square root of the summed errors in each of the carbon pools listed in the Framework Module. For modeled results, the uncertainty in the input inventory data and model structural uncertainty shall be considered as discussed below. The total baseline uncertainty in each pool can be weighted by the size of the pool so that projects may reasonably target a lower precision level for pools that comprise only a small proportion of the total stock as follows:

$$Uncertainty_{BSL,SS,i} = \frac{\sqrt{(U_{BSL,SS1,i}*E_{BSL,SS1,i})^2 + (U_{BSL,SS2,i}*E_{BSL,SS2,i})^2 + \dots + (U_{BSL,SSn,i}*E_{BSL,SSn,i})^2}}{E_{BSL,SS1,i} + E_{BSL,SS2,i} + \dots + E_{BSL,SSn,i}}$$
(38)

⁶⁴ Park, H. M. 2010. Hypothesis testing and statistical power of a test. Technical Working Paper. University Information Technology Services (UITS) Center for Statistical and Mathematical Computing, Indiana University. http://www.indiana.edu/~statmath/stat/all/power/power.pdf.

⁶⁵ Silva LCR, Corrêa RS, Doane TA, Pereira EIP, Horwath WR (2013) Unprecedented carbon accumulation in mined soils: the synergistic effect of resource input and plant species invasion. Ecological Applications 23:1345–1356.

(MM-W/R) (MODEL-W/R) (X-UNC) (TOOLS)

where:

Uncertainty _{BS}	<i>SL,SS,i</i> is the percentage uncertainty of the combined carbon stocks and greenhouse gas sources for the uncertainty baseline case in stratum <i>i</i> (%);
U _{BSL,SS,i}	is the percentage uncertainty (expressed as 90% confidence interval as a percentage of the mean where appropriate) of carbon stocks and greenhouse gas sources for the baseline case in stratum <i>i</i> (1,2n represent different carbon pools and/or GHG sources) (%);
E _{BSL,SS,i}	is the carbon stock in stratum <i>i</i> (1,2n represent different carbon pools and/or GHG sources) for the baseline case (t CO_2 -e); and
i	is the stratum within the project boundary (1,2,3,M).

ESTIMATION OF PROJECT UNCERTAINTY

As with baseline uncertainty, it is important that the process of project planning consider uncertainty. Procedures including stratification and the allocation of sufficient number of measurement locations can help minimize uncertainty. It is good practice to consider uncertainty at an early stage to identify the data sources with the highest risk to allow the opportunity to conduct further work to diminish uncertainty. Estimation of uncertainty for pools and emissions sources for each measurement pool requires calculation of both the mean and the 90% confidence interval. In all cases, uncertainty should be expressed at the 90% confidence interval as a percentage of the mean. The uncertainty in the project scenario should be defined as the square root of the summed errors in each of the carbon pools. For modeled results, follow guidelines discussed below. The errors in each pool can be weighted by the size of the pool so that projects may reasonably target a lower precision level for pools that comprise only a small proportion of the total stock as follows:

$$Uncertainty_{P,SS,i} = \frac{\sqrt{(U_{P,SS1,i}*E_{P,SS1,i})^2 + (U_{P,SS2,i}*E_{P,SS2,i})^2 + \dots + (U_{P,SSn,i}*E_{P,SSn,i})^2}}{E_{P,SS1,i} + E_{P,SS2,i} + \dots + E_{P,SSn,i}}$$
(39)
where:
$$Uncertainty_{P,SS,i}$$
 is the percentage uncertainty of the combined carbon stocks and greenhouse gas sources for the project scenario in stratum *i* (%);
$$U_{P,SS,i}$$
 is the percentage uncertainty (expressed at the 90% confidence interval) as a percentage of the mean where appropriate, of carbon stocks and greenhouse gases for the project scenario in stratum *i* (%); and
$$E_{P,SS,i}$$
 is the carbon stock in stratum *i* for the project carbon pools 1, 2, 3 ... M strata (t CO₂-e)

ESTIMATING UNCERTAINTY ASSOCIATED WITH EDDY COVARIANCE MEASUREMENTS

When calculating uncertainty associated with using eddy covariance to estimate emission reductions, this protocol requires project proponents to account for random measurement error and error associated with gap-filling procedures used to calculate annual sums. Systematic bias error is also discussed here but can be conservatively excluded from uncertainty deductions if quality assurance and quality control measures are appropriately followed as discussed in the emissions and carbon-stock Methods Modules (E-E and CP-S).

Random Measurement Error

Random measurement error can create substantial noise or scatter in the data and can occur due to spectral filtering effects, turbulent transport, instrumentation, and footprint issues⁶⁶. Errors can be reduced by using high sampling rates (at least 1Hz; ideally 10Hz), measuring continuously during each project year, measuring gas concentration and wind speed high enough above the vegetation, minimizing separation between sensors (<20cm), and minimizing flow distortion in the sensor array and mast⁶⁷.

Two general approaches are allowed for estimating the random error (ε_{random}),. A project proponent may use a documented and validated empirical model demonstrated to be an accurate predictor of the observed eddy covariance data. The residual between observed and modeled fluxes can give an estimate of error as long as model error is shown to be minimal⁶⁸. The project proponent may also use a daily-differencing approach where data points collected under the same environmental conditions in successive days (x_1 , x_2) are compared and the random measurement error is estimated as the standard deviation of the differences between x_1 and $x_2^{69,70}$. This method can be used in combination with Monte Carlo methods to estimate the 90% confidence interval due to random error in gap-filled net ecosystem exchange at the annual time step. It is important to note that random error associated with eddy covariance measurements typically follows a double-exponential (Laplace) distribution and not the normal (Gaussian) distribution, therefore maximum likelihood estimation techniques should be used to estimate random error confidence intervals as opposed to least squares optimization with requires normally distributed error and constant variance. Alternatively, the project proponent may also use peer-reviewed methods for estimating the random error in eddy-covariance methods.

Estimations of Random and Gap-Filling Errors Over Long Time Scales

systems. Agricultural and Forest Meteorology, 104(3): 185-198.

 ⁶⁶ Richardson, A.D. et al., 2012. Eddy covariance: a practical guide to measurement and data analysis. Springer.
 ⁶⁷ Massman, W.J., 2000. A simple method for estimating frequency response corrections for eddy covariance

⁶⁸ Richardson, A.D. and Hollinger, D.Y., 2005. Statistical modeling of ecosystem respiration using eddy covariance data: maximum likelihood parameter estimation, and Monte Carlo simulation of model and parameter uncertainty, applied to three simple models. Agricultural and Forest Meteorology, 131(3): 191-208.

⁶⁹ Liu, M. et al., 2009. Uncertainty analysis of CO₂ flux components in subtropical evergreen coniferous plantation. Science in China Series D: Earth Sciences, 52(2): 257-268.

⁷⁰ Richardson, A.D. et al., 2006. A multi-site analysis of random error in tower-based measurements of carbon and energy fluxes. Agricultural and Forest Meteorology, 136(1): 1-18.

To estimate uncertainty of annual sums for emissions and carbon stock changes associated with gapfilling using eddy covariance, project proponents shall use accepted and peer-reviewed methodologies. Monte Carlo or resampling techniques are recommended. System failure and data filtering can lead to gaps in the data which need to be filled in order to calculate annual sums. Most sites experience 35% data loss⁷¹. If more than 60% of eddy covariance data need to be gap filled, uncertainty in measurements and annual sums are excessively high and alternate measurement methods for measuring emissions and carbon stock changes must be used. There are several approaches for filling data gaps⁷². Generally, the longer the time scale of integration the smaller the uncertainty due to larger sample sizes and the dampening of outliers. Resampling techniques allowing accounting for uncertainties associated with gap-filling.

Project proponents may use the bootstrap resampling technique for estimating error associated with gap-filled annual sums ($\varepsilon_{gapfill}$) he or other appropriate peer-reviewed method. In this method, artificial datasets (of 1000-10000 data points) are created from the observed data using Monte-Carlo techniques Models used for filling gaps are then applied to those data sets. These datasets are used to calculate annual values and the variation across those data is used to estimate a 90% confidence interval around the annual carbon stock changes or GHG emissions⁷³.

Random measurement error and gap-filling error are calculated using the root-sum-square method⁷⁴ and collectively constitute the total eddy covariance uncertainty expressed as a 90% confidence interval around the annual sum, U_{EC} .

$$U_{EC} = \sqrt{\varepsilon_{random}^2 + \varepsilon_{gapfill}^2}$$
(40)

where $\varepsilon_{gapfill}$ is the 90% confidence interval associated with gap-filled annual sums and ε_{random} is the 90% confidence interval of the total random measurement uncertainty described above.

Systematic Measurement Error

Systematic measurement errors create a constant bias in the data. These errors do not need to be deducted from emission reductions using eddy covariance techniques if they are appropriately avoided or corrected for as per guidelines in the emissions and carbon-stock modules. Systematic errors or biases in the data can be avoided by calibrating instruments properly and meeting assumptions of the eddy covariance technique such as requirements of flat homogeneous terrain and ample turbulence.

⁷¹ Eva Falge, Dennis Baldocchi, Richard Olson, Peter Anthoni, Marc Aubinet, Christian Bernhofer, George Burba, Reinhart Ceulemans, Robert Clement, Han Dolman, Andre Grainer, Thomas Grunwald, David Hollinger, Niels-Otto Jensen, Gabriel Katul, Petri Keronen, Andrew Kowalski, Chun Ta Lai, Beverly E. Law, Tilden Meyers, Jon Moncrieff, Eddy Moors, J. William Munger, Kim Pilegaard, Ullar Rannik, Corinna Rebmann, Andrew E. Suyker, John Tenhunen, Kevin Tu, Shashi Verma, Timo Vesala, Kell Wilson, and Steve Wofsy, 2001, Gap filling strategies for defensible annual sums of net ecosystem exchange, Agricultural and Forest Meteorology, 107 (2001) 43–69.

⁷² Moffat, A.M. et al., 2007. Comprehensive comparison of gap-filling techniques for eddy covariance net carbon fluxes. Agricultural and Forest Meteorology, 147(3): 209-232.

⁷³ Hirano, T. et al., 2012. Effects of disturbances on the carbon balance of tropical peat swamp forests. Global Change Biology, 18(11): 3410-3422. Also Lui et al. 2009.

⁷⁴ Lui et al. 2009.

These errors are also related to advection, drainage effects, storage⁷⁵ and roving flux footprints⁷⁶ Previous work in the Delta has demonstrated flux footprint issues can create large errors eddy flux measurements⁷⁷. Other systematic biases can be avoided by correcting for high-frequency losses and density fluctuations associated with long tube lengths in closed path systems. For further discussion of systematic errors associated with eddy covariance measurements and how to avoid and correct for them see Richardson et al⁷⁸ and the Methods Module.

Estimating uncertainty in biogeochemical modeling

When using process-based biogeochemical models to estimate emission reductions, this protocol requires project proponents to account for model structural error and error associated with data inputs. The uncertainty associated with model inputs and model structural uncertainty shall be incorporated into Equations 2 and 3.

Error Associated with Data Inputs

Project proponents shall estimate random measurement and sampling error associated with data inputs for biogeochemical models^{79,80}. Where measurements are replicated in time and space within strata, pools and locations, sampling error can be calculated using the standard error of the mean value of the replicate measurements. For example, initial measurements of soil organic carbon must be replicated across strata. Those measurements will be averaged and the standard error of the mean is used to estimate the spatial uncertainty in soil organic carbon measurements. The estimated uncertainty shall be incorporated into the model uncertainty estimate.

To estimate random measurement error, measurements shall be replicated in the same location during the same timeframe. For example, if LAI is measured using a LAI-2200C Plant Canopy Analyzer (LI-COR, Lincoln, NE, USA), the variance across measurements replicated in the same location can be used to calculate the random error associated with LAI data. Random measurement and sampling errors together comprise the total error associated with each data input. The percent error associated with data inputs (*U*_{inputs}) is estimated by taking the product of the random and sample errors. Errors are expressed as 90% confidence intervals.

⁷⁵Aubinet, M. et al., 2005. Comparing CO₂ storage and advection conditions at night at different CARBOEUROFLUX sites. Boundary-Layer Meteorol, 116(1): 63-93.

⁷⁶ Aubinet, M. et al., 2005. Comparing CO₂ storage and advection conditions at night at different CARBOEUROFLUX sites. Boundary-Layer Meteorol, 116(1): 63-93; and Göckede, M., Markkanen, T., Hasager, C.B. and Foken, T., 2006. Update of a footprint-based approach for the characterisation of complex measurement sites. Boundary-Layer Meteorol, 118(3): 635-655.

⁷⁷ Baldocchi, D. et al., 2012. The challenges of measuring methane fluxes and concentrations over a peatland pasture. Agricultural and Forest Meteorology, 153(0): 177-187.

 ⁷⁸ Richardson, A.D. et al., 2012. Eddy covariance: a practical guide to measurement and data analysis. Springer.
 ⁷⁹ Keenan, T.F., Carbone, M.S., Reichstein, M. and Richardson, A.D., 2011. The model–data fusion pitfall: assuming certainty in an uncertain world. Oecologia, 167(3): 587-597, Richardson, A.D. et al., 2010. Estimating parameters of a forest ecosystem C model with measurements of stocks and fluxes as joint constraints. Ibid., 164(1): 25-40.
 ⁸⁰ Richardson, A.D. et al., 2010. Estimating parameters of a forest ecosystem C model with measurements of stocks and fluxes as joint constraints. Oecologia, 164(1): 25-40.

$$U_{inputs} = \prod_{i} (\sigma_{random_i} + \sigma_{sample_i})$$
(41)

where:

 σ_{random_i} is the 90% confidence interval associated with measurements of model inputs in stratum *i*; and

 σ_{sample_i} is the 90% confidence interval associated with sample collection in stratum *i*.

Meteorological drivers for the model such as air temperature and available light do not add significant error to the model estimations of emissions and therefore do not need to be accounted for in estimating emission reductions.

Model Structural Error

Model structure uncertainty (U_{struct}) shall be estimated by validation of the model against a year of data that is independent from the data used to calibrate the model. A minimum of 1 year of data will be used for estimates of uncertainty. There are numerous ways of estimating model output uncertainty such as bootstrapping methods discussed above. In addition a $\chi 2$ statistic can be used to determine the uncertainty of the model output. Project proponents shall document appropriate peer reviewed methods and parameters for calculating model uncertainty. As new data and updated model versions become available model structural uncertainty shall be re-evaluated.

Uncertainty Deductions to Emission Reductions

Model uncertainty must be calculated for each year when the carbon stock changes and emissions are estimated. Model estimated uncertainty deductions to emission reductions shall be calculated as follows:

$$ER_{corr} = \sqrt{U_{inputs}^2 + U_{struct}^2}$$
(42)

where:

ER _{corr}	is the total model uncertainty expressed as a 90% confidence interval around the annual sum (t CO_2 -e);
U _{inputs}	is the total uncertainty from model inputs expressed as a 90% confidence interval (t CO_2 -e); and
Ustruct	is the model structure uncertainty expressed as a 90% confidence interval (t CO_2 -e).

DATA AND PARAMETERS MONITORED

Data /parameter:	E _{BSL,SS}
Data unit:	t CO ₂ -e

Used in Equations:	38
Description	Carbon stock (e.g. soil organic carbon, and emissions if determined
	significant) for the baseline case.
Source of data:	The terms denoting significant carbon stocks or GHG emissions from
	Baseline Modules used to calculate emission reductions
Measurement	
procedures (if any):	
Monitoring	The monitoring must occur within five years before the start of the project
frequency:	activity and when the baseline is revisited.
Quality Assurance /	
Quality Control	
Any comment:	Baseline stocks and sources are estimated ex-ante for each baseline period.

Data /parameter:	E _{P,SS}
Data unit:	t CO ₂ -e
Used in Equations:	39
Description	Description: Carbon stock (e.g. soil organic carbon, and emissions if determined significant) for the project case.
Source of data:	The terms denoting significant carbon stocks, or GHG emissions used to calculate net emission reductions from the following relevant modules.
Measurement procedures (if any):	
Monitoring frequency:	Monitoring frequency may range from 5 to 20 years and can be fixed to coincide with the crediting period.
Quality Assurance / Quality Control	
Any comment:	The ex-ante estimation shall be derived directly from the estimations originating in the relevant modules:

Data /parameter:	U _{BSL,SS}
Data unit:	%
Used in Equations:	38
Description	Percentage uncertainty (expressed as 90% confidence interval as a
	percentage of the mean where appropriate) for carbon stocks and
	greenhouse gas sources in the baseline case in stratum <i>i</i> (1,2n represent
	different carbon pools and/or GHG sources)
Source of data:	Calculations arising from field measurement data.
Measurement	Uncertainty in pools derived from field measurement with 90% confidence
procedures (if any):	interval calculated as the standard error of the averaged plot measurements
	in each stratum multiplied by the t value for the 90% confidence level. For
	emission sources and wetland loss conservative parameters should be used
	sufficient to allow the uncertainty to be set as zero.
Monitoring	The monitoring must occur within five years before the start of the project
frequency:	activity and when the baseline is revisited.

Quality Assurance /	
Quality Control	
Any comment:	Baseline stocks and sources are estimated ex-ante for each baseline period.

Data /parameter:	U _{P,SS}
Data unit:	%
Used in Equations:	39
Description	Percentage uncertainty (expressed as 90% confidence interval as a percentage of the mean where appropriate) for carbon stocks and greenhouse gas sources in the baseline case in stratum <i>i</i> (1,2n represent different carbon pools and/or GHG sources)
Source of data:	Calculations arising from field measurement data.
Measurement procedures (if any):	Uncertainty in pools derived from field measurement with 90% confidence interval calculated as the standard error of the averaged plot measurements in each stratum multiplied by the t value for the 90% confidence level. For emission sources and wetland loss conservative parameters should be used sufficient to allow the uncertainty to be set as zero.
Monitoring frequency:	Monitoring frequency may range from 5 to 20 years and can be fixed to coincide with the crediting period.
Quality Assurance / Quality Control	
Any comment:	<i>Ex-ante</i> the uncertainty in the with-project carbon stocks and sources shall be equal to the calculated baseline uncertainty

(T-RISK) Methodological Module Tool for estimation of non-permanence risk for wetland construction and restoration and rice cultivation in the Sacramento-San Joaquin Delta and San Francisco Estuary

The project will employ the non-permanence risk tool currently approved by ACR as referenced in the ACR Standard.

(T-SIG) Methodological Module Tool for significance testing for wetland construction and restoration and rice cultivation in the Sacramento-San Joaquin Delta and San Francisco Estuary

The currently acceptable significance testing tool is the Clean Development Mechanism (CDM) tool for testing significance of GHG emissions which can be found at:

http://cdm.unfccc.int/methodologies/ARmethodologies/tools/ar-am-tool-04-v1.pdf/history_view_

(T-PLOT) Methodological Module Tool for the calculation of the number of sample plots for measurements for wetland construction and restoration and rice cultivation in the Sacramento-San Joaquin Delta and San Francisco Estuary

The currently acceptable tool is the Clean Development Mechanism (CDM) tool for calculation of the number of sample plots for measurements which can be found at:

http://cdm.unfccc.int/methodologies/ARmethodologies/tools/ar-am-tool-03-v2.1.0.pdf/history_view_

(MM-W/R) (MODEL-W/R) (X-UNC) (TOOLS)

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