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Supporting Information for

**Coupling Remote Sensing with a Process Model for the Simulation of Rangeland Carbon Dynamics**

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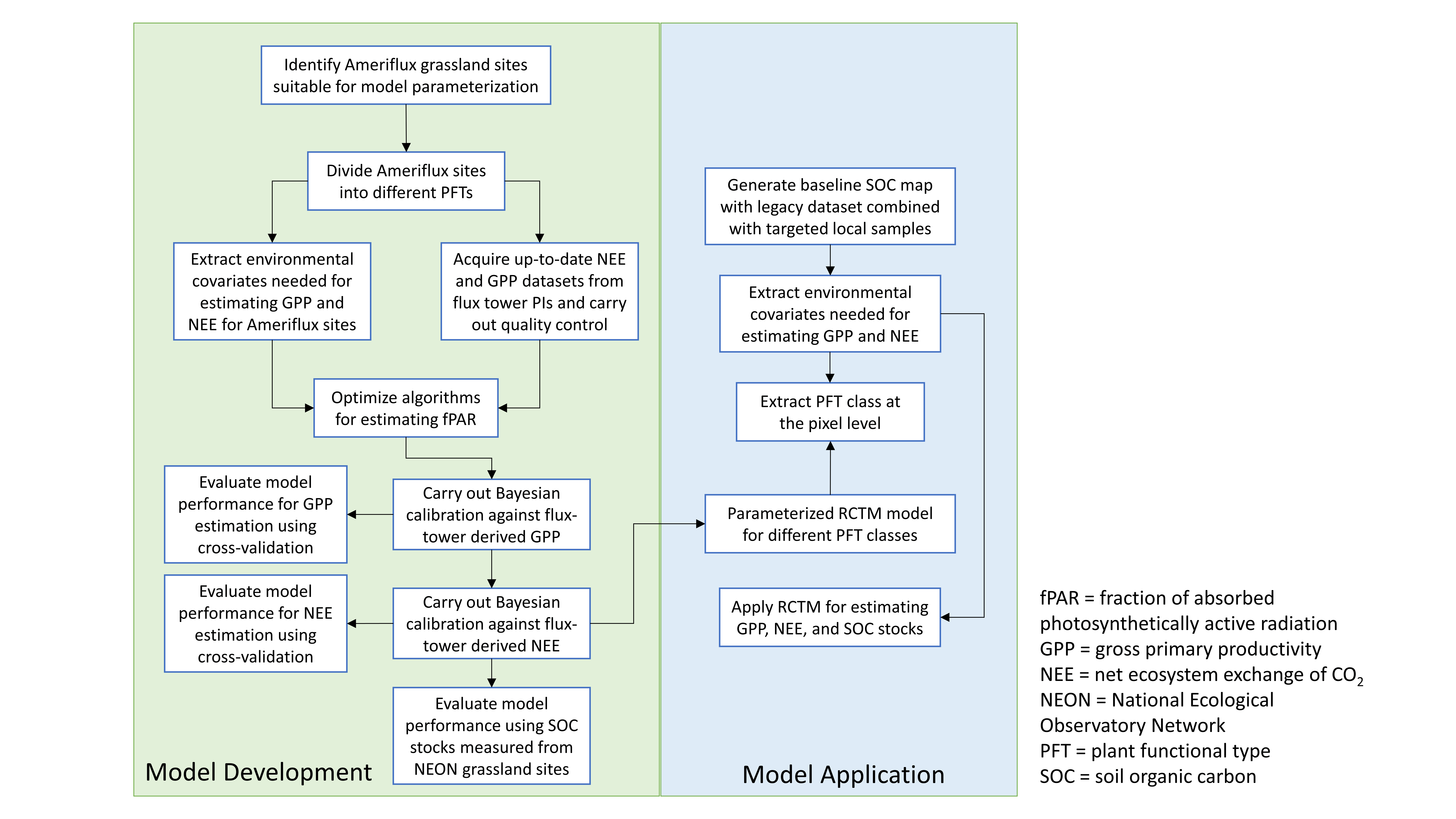
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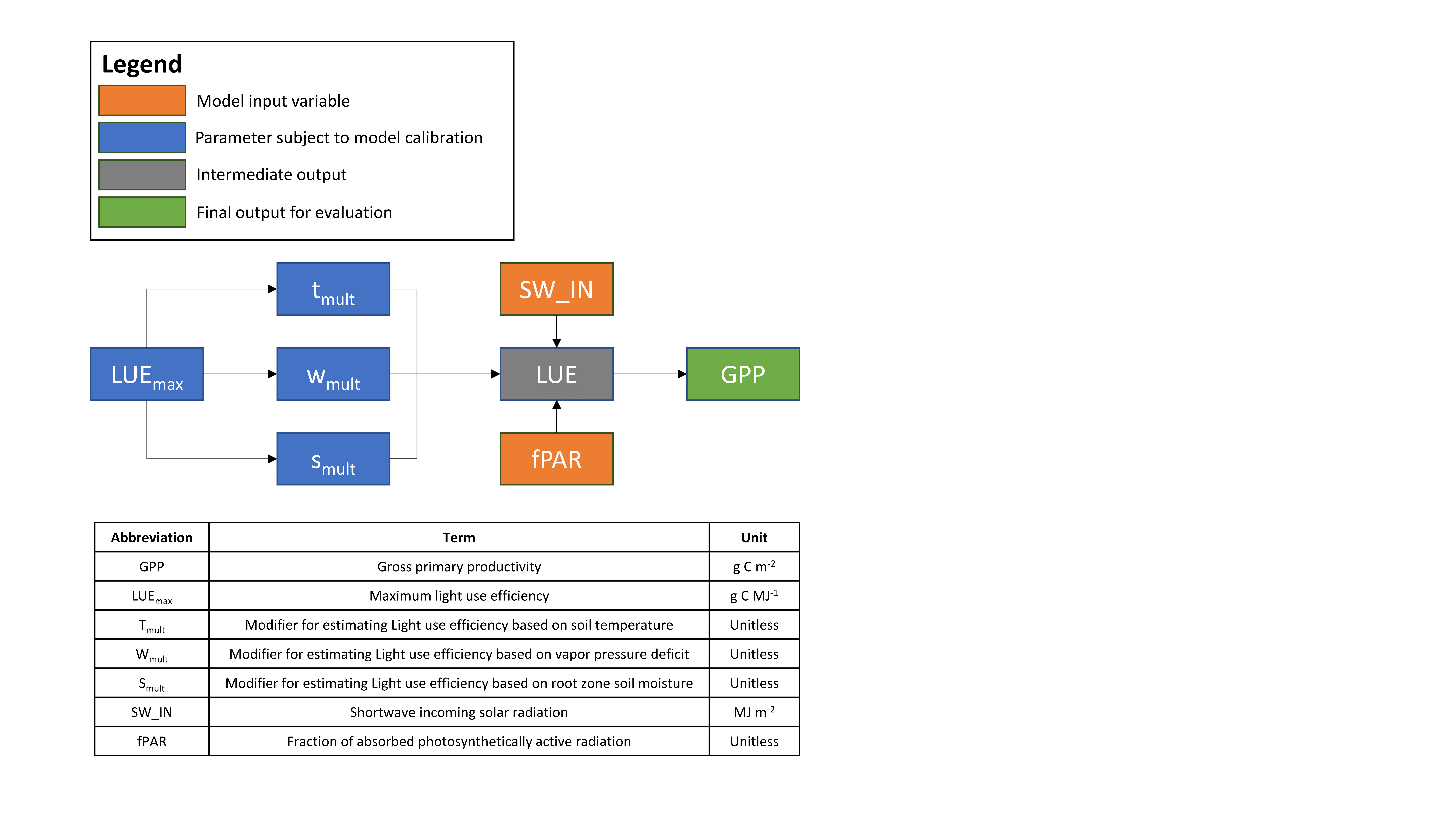
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Appendices A to G

Appendix A: Flowcharts and diagrams illustrating the modeling process



**Figure. A1** Flowchart showing the procedure for the development and application of the Rangeland Carbon Tracking and Monitoring (RCTM) System.



**Figure. A2** Diagram showing the procedure and parameters associated with gross primary productivity (GPP) estimation within the Rangeland Carbon Tracking and Monitoring (RCTM) System.

A computer screen shot of a diagram

Description automatically generated

**Figure. A3** Diagram showing the procedure and parameters associated with net ecosystem exchange (NEE) and soil organic carbon (SOC) estimation within the Rangeland Carbon Tracking and Monitoring (RCTM) System.

**Table. A1** Description of process-based models that were used to develop model structure and algorithms in the Rangeland Carbon Tracking and Monitoring (RCTM) System.

|  |  |  |  |
| --- | --- | --- | --- |
| Model | Model description a | Usage in RCTM | Reference |
| Soil Moisture Active-Passive (SMAP)-Level 4 Carbon (L4C) model | The L4C model provides global daily estimates of the terrestrial C budget, including NEE, GPP, RECO, and surface SOC stocks through the use of remote sensing inputs and environmental constraints. | The light use efficiency algorithms in RCTM were adapted from L4C where environmental constraints were modified to reflect main drivers for rangeland productivity. | Endsley et al. (2020) |
| DAYCENT model | The DAYCENT model simulates daily C and N fluxes between the terrestrial ecosystem and the atmosphere. The model contains submodules simulating soil water and heat dynamics, plant growth, litter and SOM decomposition, nutrient cycling, and GHG fluxes from soils using environmental and management input datasets. | The litter decomposition as a function of time, soil temperature, and moisture condition in RCTM were adapted from DAYCENT where coefficients associated with environmental constraints were parameterized using flux tower datasets. | Parton et al. (1998) |
| Rothamsted Carbon (RothC) model | The RothC model estimates the turnover of SOM as a function of C inputs and environmental constraints on a monthly time step. The SOM pools are divided into four active compartments and one inert compartment. | The measurable SOM pools (particulate organic carbon, mineral-associated organic carbon, and inert organic carbon) conceptualized in RCTM were adapted from the RothC structure. | Coleman & Jenkinson (1996) |

a C = carbon; GHG = greenhouse gas; GPP = gross primary productivity; NEE = net ecosystem exchange; RECO = ecosystem respiration; SOC = soil organic carbon; SOM = soil organic matter.

Appendix B: Details about the Ameriflux and NEON sites used in model parameterization

**Table. B1** Ameriflux (<https://ameriflux.lbl.gov/>) and NEON (<https://www.neonscience.org/>) sites retained for model calibration and validation. The criteria for site selection were described in detail in the main manuscript.

|  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Site | Location | Time frame a | Data  availability | | Grid size d | MAP (mm) e | MAT (°C) f | Soil group g | Land use/cover type h | | | Vegetation type i |
| Flux data b | Soil data c | NLCD | RAP | Additional descriptions or history |
| A32 | 36.82, -97.82 (OK) | 2015-2017 | NEE | SM, ST | Small | 851 | 16 | Argiustolls | GRA | PG | Grassland cut for hay | MHP |
| AR1 | 36.43, -99.42 (OK) | 2009-2012 | NEE, GPP | SM, ST | Small | 530 | 15 | Haplustepts | GRA | PG | Converted from native prairie to switchgrass | PAG |
| AR2 | 36.64, -99.60 (OK) | 2009-2012 | NEE, GPP | SM, ST | Small | 501 | 15 | Ustipsamments | CRO | PG | Converted from wheat to switchgrass | PAG |
| ARb | 35.55, -98.04 (OK) | 2005-2006 | NEE | SOC | Small | 706 | 16 | Paleustolls | GRA | PG | Native prairies with light grazing activities | PAG |
| ARc | 35.55, -98.04 (OK) | 2005-2006 | NEE | NR | Small | 706 | 16 | Paleustolls | GRA | PG | Native prairies with light grazing activities | PAG |
| Aud | 31.59, -110.51 (AZ) | 2004-2009 | NEE, GPP | SM, ST | Small | 418 | 17 | Haplargids | GRA | PG | Non grazed perennial grassland | PAG |
| Bkg | 44.35, -96.84 (SD) | 2005-2008 | NEE, GPP | SM, ST | Small | 666 | 7 | Hapludolls | HP | PG | Actively grazed grassland | PAG |
| BMM | 45.78, -110.78 (MT) | 2016-2017 | NEE, GPP | SM, ST | Small | 1170 | 4 | Argicryolls | GRA | PG | Non grazed perennial grassland | PAG |
| BRG | 39.22, -86.54 (IN) | 2017-2020 | NEE, GPP | SM, ST | Small | 1295 | 12 | Hapludalfs | HP | PG | grassland with mixed species | PAG |
| Cop | 38.09, -109.39 (UT) | 2001-2007 | NEE | SM, ST | Small | 340 | 11 | Haplocalcids | GRA | BG and PG | Grazed grassland with significant presence of shrub and bare ground | GSM |
| Ctn | 43.95, -101.85 (SD) | 2007-2008 | NEE, GPP | SM, ST | Small | 517 | 9 | Torrerts | GRA | PG | Grazed perennial grassland | PAG |
| CZ1 | 37.11, -119.73 (CA) | 2006-2018 | NEE | SM, ST | Small | 506 | 17 | Haploxeralfs | SHB | AG | Woodland with occasionally grazed grass | GTM |
| Dia | 37.68, -121.53 (CA) | 2010-2013 | NEE | SM, ST | Small | 341 | 16 | Haploxererts | GRA | AG | Non-grazed annual grassland | PAG |
| Fpe | 29.95, -98.00 (TX) | 2004-2006 | NEE, GPP | SM, ST | Small | 1032 | 20 | Haplustolls | GRA | PG | Grazed perennial grassland | PAG |
| Fwf | 35.45, -111.77 (AZ) | 2005-2011 | NEE, GPP | SM, ST | Small | 501 | 8 | Haplustalfs | TREE | PG and BG | Forest replaced by grassland | GTM |
| Hn1 | 46.41, -119.28 (WA) | 2016-2017 | NEE | SM, ST | Small | 231 | 12 | Camborthids | SHB | AG | A mixture of shrub and grass | GSM |
| Hn2 | 46.69, -119.46 (WA) | 2016-2017 | NEE | SM | Small | 244 | 13 | Haploxerolls | SHB | PG | Grassland dominated by invasive perennial and annual species | PAG |
| IB2 j | 41.84, -88.24 (IL) | 2005-2007 | NEE, GPP | SM, ST | Small | 870 | 10 | Hapludalfs | TREE | PG | Non-grazed perennial grassland | PAG |
| Jo1 | 32.58, -106.64 (NM) | 2011-2020 | NEE, GPP | SM, ST, SOC | Small | 299 | 16 | Haplargids | GRA | BG | Grassland deterioration accompanied by transition to shrubland | GSM |
| KFS | 39.06, -95.19 (KS) | 2007-2019 | NEE | SM | Small | 1062 | 13 | Argiudolls | GRA | PG | Perennial grassland historically under intensive agriculture | PAG |
| KLS | 38.77, -97.57 (KS) | 2012-2018 | NEE | SM, ST | Small | 791 | 14 | Haplustolls | CRO | PG | Perennial wheatgrass | PAG |
| KM2 | 42.44, -85.31 (MI) | 2009-2019 | NEE, GPP | SM, ST, SOC | Small | 1109 | 9 | Hapludalfs | HP | PG | Restored prairie | PAG |
| KM3 | 42.45, -85.31 (MI) | 2009-2018 | NEE, GPP | SM, ST, SOC | Small | 1109 | 9 | Hapludalfs | CRO | PG | Switchgrass | PAG |
| KM4 | 42.44, -85.33 (MI) | 2009-2019 | NEE, GPP | ST, SOC | Small | 1108 | 9 | Hapludalfs | HP | PG | Perennial grassland under Conservation Reserve Program | PAG |
| Kon | 39.08, -96.56 (KS) | 2004-2015 | NEE | SM, ST | Small | 998 | 12 | Paleustolls | GRA | PG | Native tallgrass prairie | PAG |
| LS1 | 31.56, -110.14 (AZ) | 2003-2008 | NEE, GPP | SM, ST | Large | 341 | 18 | Torrifluvents | SHB | PG | Riparian grassland dominated by perennial grass | PAG |
| LS2 | 31.57, -110.13 (AZ) | 2003-2008 | NEE, GPP | SM, ST | Large | 341 | 18 | Haplargids | SHB | PG and TREE | Riparian grassland dominated by shrub and perennial grass | GSM |
| Mpj | 34.44, -106.24 (NM) | 2008-2022 | NEE, GPP | SM, ST | Large | 431 | 11 | Haplustalfs | TREE | TREE | Perennial grassland with significant tree coverage | GTM |
| RFW | 39.88, -105.22 (CO) | 2011-2012 | NEE, GPP | SM, ST | Small | 426 | 11 | Argiustolls | GRA | PG | Minimally disturbed perennial grassland | PAG |
| Rls | 43.14, -116.74 (ID) | 2014-2019 | NEE, GPP | SM, ST | Small | 470 | 9 | Argixerolls | SHB | PG | Grazed sagebrush site with native grass and forbs | GSM |
| Rms | 43.06, -116.75 (ID) | 2014-2019 | NEE, GPP | SM, ST | Small | 682 | 7 | Haplocryolls | SHB | SHB and PG | Grazed sagebrush and grass site | GSM |
| Ro4 | 44.68, -93.07 (MN) | 2014-2019 | NEE, GPP | SM, ST | Small | 1016 | 7 | Hapludalfs | HP | PG | Restored prairie dominated by perennial grass | PAG |
| Rwe | 43.07, -116.76 (ID) | 2003-2007 | NEE, GPP | ST | Small | 637 | 6 | Cryoborolls | SHB | PG | Grazed sagebrush and grass site | GSM |
| Rwf | 43.12, -116.72 (ID) | 2014-2019 | NEE, GPP | SM, ST | Small | 657 | 7 | Argixerolls | SHB | PG | Recovering sagebrush site with perennial grass burned in 2007 | GSM |
| Rws | 43.17, -116.71 (ID) | 2014-2020 | NEE, GPP | SM, ST | Small | 425 | 9 | Durargids | SHB | PG | Sagebrush site with grazed grassland | GSM |
| SCg | 33.74, -117.69 (CA) | 2006-2018 | NEE | SM, ST | Small | 333 | 19 | Haploxerolls | SHB | PG and AG | Grassland historically dominated by annual grass and underwent restoration with a focus on establishing perennial native grass | PAG |
| SdH | 42.07, -101.41 (NE) | 2004-2010 | NEE | SM, ST | Small | 612 | 9 | Ustipsamments | WET | PG | Grazed mix species prairie | PAG |
| Seg | 34.36, -106.70 (NM) | 2007-2022 | NEE, GPP | SM, ST | Small | 277 | 14 | Haplocalcids | GRA | BG and PG | Non-grazed mix species grassland with shrub that was historically grazed | GSM |
| Ses | 34.33, -106.74 (NM) | 2007-2022 | NEE, GPP | SM, ST | Small | 266 | 14 | Torriorthents | SHB | BG | Site with shrub and grazed grassland | GSM |
| Snd | 38.04, -121.75 (CA) | 2007-2015 | NEE | SM, ST | Small | 357 | 17 | Haploxerolls | CRO | PG and AG | Peatland pasture with heavy grazing | MHP |
| SRM | 31.82, -110.87 (AZ) | 2004-2020 | NEE, GPP | SM, ST | Small | 386 | 19 | Haplargids | SHB | SHB | Moderately-grazed grassland encroached by shrub | GSM |
| Ton | 38.43, -120.97 (CA) | 2001-2021 | NEE, GPP | SM, ST | Small | 627 | 17 | Haploxeralfs | GRA | AG | Site with tree and grazed grassland | GTM |
| Tx1 | 30.62, -97.29 (TX) | 2020-2020 | NEE, GPP | SM, ST | Small | 748 | 21 | Haplusterts | HP | PG | Grazed mixed species pasture | MHP |
| Tx2 | 31.48, -96.88 (TX) | 2020-2020 | NEE, GPP | SM, ST | Small | 1502 | 20 | Haplusterts | HP | PG | Grazed mixed species g pasture | MHP |
| Var | 38.41, -120.95 (CA) | 2000-2021 | NEE, GPP | SM, ST | Small | 635 | 17 | Haploxeralfs | GRA | AG | Dominated by annual grass | PAG |
| Wdn | 40.78, -106.26 (CO) | 2006-2008 | NEE | SM, ST | Small | 412 | 4 | Haplargids | SHB | SHB and PG | Sagebrush site with grassland | GSM |
| Wjs | 34.43, -105.86 (NM) | 2007-2022 | NEE, GPP | SM, ST | Large | 332 | 12 | Haplargids | SHB | BG | Intermittently grazed perennial grassland | PAG |
| Wkg | 31.74, -109.94 (AZ) | 2004-2021 | NEE, GPP | SM, ST, SOC | Small | 410 | 16 | Haplargids | SHB | PG | Grazed perennial grassland with scattered shrubs | GSM |
| xAE | 35.41, -99.06 (OK) | 2019-2022 | NEE, GPP | SM, ST, SOC | Large | 720 | 16 | Ustorthents | GRA | PG | Grazed perennial grassland | PAG |
| xCL | 33.40, -97.57 (TX) | 2019-2022 | NEE, GPP | SM, ST, SOC | Large | 927 | 18 | Paleustalfs | TREE | TREE | Site with tree and grazed grassland | GTM |
| xCP | 40.82, -104.75 (CO) | 2019-2021 | NEE, GPP | SM, ST, SOC | Large | 331 | 9 | Argiustolls | GRA | PG | Moderately grazed perennial grassland | PAG |
| xDC | 47.16, -99.11 (ND) | 2018-2021 | NEE, GPP | SM, ST, SOC | Large | 512 | 5 | Haplustolls | GRA | PG | Grazed perennial grassland | PAG |
| xJR | 32.59, -106.84 (NM) | 2018-2021 | NEE, GPP | SM, ST, SOC | Large | 247 | 17 | Calciargids | SHB | PG and BG | Grazed grassland encroached with shrub | GSM |
| xKA | 39.11, -96.61  (KS) | 2018-2021 | NEE, GPP | SM, ST, SOC | Large | 1044 | 13 | Haplustolls | CRO | PG | Native prairie | PAG |
| xKZ | 39.10, -96.56 (KS) | 2018-2021 | NEE, GPP | SM, ST, SOC | Large | 1124 | 12 | Argiustolls | GRA | PG | Native prairie | PAG |
| xMB | 38.25, -109.39 (UT) | 2020-2021 | NEE, GPP | SM, ST, SOC | Large | 255 | 12 | Haplocalcids | GRA | BG | Site with shrub and grazed grassland | GSM |
| xNG | 46.77, -100.92 (ND) | 2018-2021 | NEE, GPP | SM, ST, SOC | Large | 500 | 6 | Argiustolls | GRA | PG | Native grassland dominated by perennial grass | PAG |
| xNQ | 40.18, -112.45 (UT) | 2019-2022 | NEE, GPP | SM, ST, SOC | Large | 328 | 10 | Haplargids | SHB | PG | Site with sagebrush and grazed grassland | GSM |
| xSJ | 37.11, -119.73 (CA) | 2019-2021 | NEE, GPP | SM, ST, SOC | Large | 445 | 17 | Haploxeralfs | TREE | AG | Site with tree and lightly grazed grassland dominated by perennial grass | GTM |
| xWD | 47.13, -99.24 (ND) | 2018-2021 | NEE, GPP | SM, ST, SOC | Large | 508 | 5 | Hapludolls | CRO | PG | Restored prairie dominated by lightly grazed perennial grassland | PAG |
| xYE k | 44.95, -110.54 (WY) | 2018-2021 | NEE, GPP | SM, ST, SOC | Large | 577 | 3 | Haplocryolls | TREE | PG | Sagebrush site with mixed grass species and tree | GSM |

a Time period where flux measurements are available. Data after 2022 were not included due to the timeline of this project.

b GPP = gross primary productivity; NEE = net ecosystem exchange.

c SM = soil moisture; SOC = soil organic carbon; ST = soil temperature.

d A threshold value of 8m based on the flux tower height was used to determine the small (90 m 90 m) or large (510 m 510 m) grid sizes. These two sizes were determined empirically, considering the correlation established between tower height and the footprint at a 90% probability for sites with available footprint data.

e The mean annual precipitation (MAP) was determined using the DAYMET V4 dataset based on the NEE measurement period of each study site.

f The mean annual temperature (MAT) was determined using the DAYMET V4 dataset based on the NEE measurement period of each study site.

g The dominant soil great group for each site was extracted from OpenLandMap.

h The dominant National Land Cover Database (NLCD) extracted for the study sites included grassland (GRA), cultivated cropland (CRO), shrubland (SHB), forest (TREE), hay and pasture (HP), and wetland (WET). The dominant Rangeland Analysis Platform (RAP) vegetation cover extracted for the study sites included perennial grass (PG), annual grass (AG), bare ground (BG), shrub (SHB), and tree (TREE). Additional descriptions of the site were obtained from flux tower PIs, literature, and website information.

i The final assigned vegetation types for this work include perennial and/or annual grass (PAG), grass-shrub mixture (GSM), grass-tree mixture (GTM), and managed hay and pasture (MHP) classes.

j The flux dataset is available for a longer period (2005-2018), but only the time period with partitioned GPP data was retained for this work.

k The site is categorized under thegrass-shrub mixture class for model calibration but is considered a combination of grass-shrub mixture and grass-tree mixture for model simulation considering the significant presence of both tree and shrub.

**Table. B2** Number of sites and observations retained for net ecosystem exchange (NEE) and gross primary productivity (GPP) models divided by vegetation classes. The numbers are presented for using Spatial and Temporal Adaptive Reflectance Fusion Model (STARFM)-based inputs and MODIS-based inputs separately.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Vegetation class | NEE model | | | GPP model | | |
| Site num | Site-year num | Daily obs. num | Site num | Site-year num | Daily obs. num |
| STARFM inputs |  |  |  |  |  |  |
| Perennial and/or annual grass sites | 33 | 179 | 11,222 | 24 | 133 | 9,933 |
| Managed hay and pasture sites | 4 | 13 | 518 | 3 | 5 | 354 |
| Grass and shrub mixed sites | 17 | 127 | 8,119 | 15 | 119 | 10,496 |
| Grass and tree mixed sites | 5 | 45 | 2,961 | 5 | 45 | 3,456 |
| MODIS inputs |  |  |  |  |  |  |
| Perennial and/or annual grass sites | 33 | 187 | 14,586 | 23 | 132 | 5,946 |
| Managed hay and pasture sites | 4 | 13 | 663 | 2 | 2 | 80 |
| Grass and shrub mixed sites | 18 | 128 | 10,229 | 14 | 116 | 5,389 |
| Grass and tree mixed sites | 6 | 58 | 4,290 | 5 | 46 | 1,982 |

**Table. B3** Model simulated changes in net ecosystem exchange (NEE), gross primary productivity (GPP), and soil organic carbon (SOC) stocks for the retained Ameriflux and NEON sites with Spatial and Temporal Adaptive Reflectance Fusion Model (STARFM)-based inputs.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Sites and vegetation classes | NEE (g C m-1 year-1) | | GPP (g C m-1 year-1) | | SOC (g C m-1 year-1) | |
| Significance | Slope | Significance | Slope | Significance | Slope |
| Perennial and/or annual grass sites | | | | | | |
| AR1 | NS | -0.2 | NS | -0.2 | \*\* | -2.5 |
| AR2 | NS | 0.5 | NS | -3.5 | \*\* | -7.9 |
| ARb | NS | -0.5 | NS | -0.5 | \*\* | 11.7 |
| ARc | NS | -0.5 | NS | -0.5 | \*\* | 11.9 |
| Aud | NS | 0.5 | NS | 5.5 | \*\* | 9.6 |
| Bkg | NS | 0.2 | NS | 6.0 | \*\* | 13.2 |
| BMM | NS | 2.0 | NS | 2.0 | NS | 1.0 |
| BRG | NS | 0.3 | NS | -2.5 | \*\* | -19.5 |
| Ctn | NS | -0.5 | NS | 7.0 | \*\* | 21.3 |
| Dia | NS | 3.0 | NS | -2.0 | NS | 0.4 |
| FPe | NS | 0.05 | NS | 0.5 | \*\* | 4.1 |
| Hn2 | NS | 0.05 | NS | 0.4 | \*\* | 0.8 |
| IB2 | NS | 2.0 | \*\* | 19.5 | \*\* | 23.8 |
| KFS | NS | -0.5 | NS | 7.0 | \*\* | 5.9 |
| KLS | NS | -1.5 | NS | -1.5 | NS | -0.2 |
| KM2 | \* | 3.5 | \*\* | 21.5 | \*\* | 21.0 |
| KM3 | \* | 3.5 | \*\* | 22.0 | \*\* | 21.7 |
| KM4 | NS | 2.0 | \* | 12.0 | \*\* | 19.7 |
| LS1 | NS | 0.5 | \*\* | 9.0 | \*\* | 9.8 |
| RFW | NS | 0.2 | NS | 1.0 | \*\* | 2.4 |
| Ro4 | NS | 0.5 | NS | 4.0 | NS | 2.4 |
| SCg | NS | 0.3 | NS | -9.5 | \*\* | -17.6 |
| SdH | NS | 0.3 | NS | 3.0 | \*\* | 7.6 |
| Var | NS | 2.5 | NS | 1.5 | \* | -4.0 |
| Wjs | NS | -0.1 | NS | -0.3 | \*\* | 2.5 |
| xAE | NS | 0.5 | NS | -1.5 | NS | 2.0 |
| xNG | NS | -1.5 | NS | 4.0 | \*\* | 19.1 |
| xWD | NS | 1.0 | NS | -0.5 | NS | -0.4 |
| Averaged results | NS | 0.5 | \* | 6.2 | \*\* | 4.7 |
| Managed hay and pasture sites | | | | | | |
| A32 | NS | 1.5 | NS | 2.5 | NS | 0.8 |
| Snd | NS | -0.5 | NS | -6.5 | \*\* | -7.2 |
| Tx1 | NS | 1.5 | NS | 8.5 | \*\* | 14.8 |
| Tx2 | NS | 2.5 | NS | 7.5 | \*\* | 16.2 |
| Averaged results | NS | 2.4 | NS | 5.4 | NS | 6.2 |
| Grass and shrub mixed sites | | | | | | |
| Cop | NS | -0.1 | NS | -0.5 | \*\* | 4.9 |
| Jo1 | NS | 0.2 | NS | 1.5 | \*\* | 4.1 |
| LS2 | NS | 1.0 | \* | 16.5 | \*\* | 16.7 |
| Rls | NS | 1.5 | NS | 7.0 | \*\* | 6.2 |
| Rms | NS | 0.5 | NS | -0.5 | \*\* | 15.9 |
| Rwe | NS | 0.5 | NS | -0.3 | \*\* | 16.9 |
| Rwf | NS | 1.0 | NS | 0.2 | \*\* | 11.4 |
| Rws | NS | 1.0 | NS | 5.0 | \*\* | 9.4 |
| Seg | NS | -0.1 | NS | 0.5 | \*\* | 1.9 |
| Ses | NS | 0.2 | NS | 1.0 | \*\* | 2.0 |
| SRM | NS | 1.0 | \* | 10.5 | \*\* | 6.5 |
| Wdn | NS | -0.3 | NS | 1.0 | NS | 1.0 |
| Wkg | NS | 1.0 | \* | 11.0 | \*\* | 25.9 |
| xJR | NS | -0.5 | NS | -1.0 | \*\* | 18.5 |
| xMB | NS | -0.02 | NS | 0.02 | \*\* | 2.5 |
| xNQ | NS | 1.5 | NS | 3.5 | NS | -0.07 |
| xYE | NS | 1.5 | NS | 3.0 | \* | 3.2 |
| Averaged results | NS | 1.2 | \* | 5.4 | \*\* | 8.4 |
| Grass and tree mixed sites | | | | | | |
| Fwf | NS | 0.4 | NS | 0.3 | \*\* | 5.0 |
| Mpj | NS | 0.4 | NS | 3.5 | \*\* | 5.0 |
| Ton | NS | 1.5 | NS | 3.0 | NS | 1.3 |
| xCL | NS | 2.0 | NS | 12.5 | \*\* | 15.3 |
| xSJ | NS | 0.5 | NS | -5.5 | \*\* | -2.8 |
| Averaged results | NS | 0.7 | NS | 3.5 | \*\* | 2.8 |

\* The slope is significantly different from zero at *P* < 0.05.

\*\* The slope is significantly different from zero at *P* < 0.01.

NS: The slope is not significantly different from zero at *P* < 0.05.

Appendix C: Model performance using MODIS and fused Landsat-MODIS inputs

We compared two strategies for model calibration and validation. The first strategy was to use Moderate Resolution Imaging Spectroradiometer (MODIS) fraction of absorbed photosynthetically active radiation (fPAR) inputs (Myneni et al., 2021) directly, while the second strategy was to use inputs fused from 30 m Landsat (Kovalskyy & Roy, 2013; Roy et al., 2014; Williams et al., 2006) and 500 m MODIS (Schaaf & Wang, 2015) through the Spatial and Temporal Adaptive Reflectance Fusion Model (STARFM) (Gao et al., 2006; Watts et al., 2011). The output of the STARFM process is synthetic 30 m imagery that retains important temporal information from MODIS and the higher spatial information from Landsat. The main report text focuses on carbon model outcomes using STARFM-based inputs, whereas here we present more information about the resulting MODIS-driven carbon model outputs.

C.1 Methodology

First, a MODIS-derived, quality controlled coarse spatial resolution fPAR data product (500 m, every 4 days) (Myneni et al., 2021) was used directly for gross primary productivity (GPP) calibration. This level-4 data product selects the highest-quality pixel from all acquisitions of both MODIS sensors and has temporal coverage dating back to 2002. We excluded cloudy pixels together with those identified with detector or other quality issues according to the associated bitmasks and quality control bands. The input variable datasets (**Table 1**) including North American Land Data Assimilation System (NLDAS)-derived shortwave incoming solar radiation (SW\_IN), soil moisture, soil temperature (Xia et al., 2012), SoilGrid+ product-based estimates of clay contents (Ramcharan et al., 2018), as well as DAYMET V4-based vapor pressure deficit (VPD) (Thornton et al., 2022), which are the same as those used in STARFM inputs-based model calibration and estimations, were merged with MODIS fPAR to generate MODIS-based input datasets for calibration at an interval of every 4 days.

Next, the MODIS-based input datasets were joined with the vegetation type-specific GPP and NEE measures processed from Section 2.3 to derive calibration datasets. As was done for STARFM input-based GPP and NEE calibration, the model initialization and parameterization procedure was implemented using the BayesianTools package in R (Hartig et al., 2023). Three Markov chain Monte Carlo chains were run in parallel for 5000 iterations to obtain posterior distributions of model parameters. Vegetation type -based model fits and results from leave-one-out cross-validation (LOOCV) were reported for perennial and/or annual grass, grass-shrub mixture, grass-tree mixture, and managed hay and pasture sites.

C.2 Results and Discussion

The MODIS-based GPP calibration results shown in **Fig. C1** was generally lower than those shown in **Fig. 3** using STARFM-based fPAR inputs. The difference of model performance was most pronounced for the grass-tree mixture sites, meaning that STARFM inputs are more accurate at reflecting spatial and temporal changes in vegetation greenness for grass-tree mixed sites. In contrast, model performance for estimating daily NEE was better for perennial and/or annual grass sites using MODIS (**Fig. C2**) than STARFM -based fPAR inputs (**Fig. 5**). This might be explained by the fact that NEE estimates depend not only on model inputs for the current day but also on those from the preceding time period. An advantage of the MODIS imagery is having repeat image retrievals at sub-weekly timesteps, which better captures changes in vegetation. Whereas it is likely that even with the complex STARFM approach some of the temporal signals from MODIS may be lost. The other difference is that, for the STARFM outputs, we estimate fPAR using a simple linear regression approach, compared to MODIS fPAR which is obtained using sophisticated radiative models (Myneni et al., 2021). Additionally, the STARFM minimum and maximum fPAR reference values were determined based on validation of calculated GPP with Ameriflux site-based GPP. Therefore, these reference values likely contained some bias towards sites with partitioned flux data, which would reduce STARFM NEE accuracy for sites without GPP. For managed hay and pasture, grass-shrub mixture, and grass-tree mixture sites, the STARFM-based model still outperformed the MODIS-based model.

A diagram of a diagram of grass

Description automatically generated with medium confidence

**Figure. C1** The gross primary productivity (GPP) model performance shown as coefficient of determination (R2), root mean square error (RMSE, C m-2 day-1), and mean bias error (MBE, C m-2 day-1) for different vegetation classes including (a) perennial and annual grass, (b) managed hay and pasture, (c) mixture of grass and shrub, and (d) mixture of grass and tree classes. Both model fits and leave-one-out cross-validation (LOOCV) results are presented. Different colors represent different Ameriflux/NEON study sites. The fraction of absorbed photosynthetically active radiation values used as model inputs for GPP estimates are directly extracted from MODIS.

A graph of different types of grass

Description automatically generated

**Figure. C2** The net ecosystem exchange (NEE) model performance shown as coefficient of determination (R2), root mean square error (RMSE, C m-2 day-1), and mean bias error (MBE, C m-2 day-1) for different vegetation classes including (a) perennial and annual grass, (b) managed hay and pasture, (c) mixture of grass and shrub, and (d) mixture of grass and tree classes. Positive NEE sign denotes ecosystem C sink activity. Both model fits and leave-one-out cross-validation (LOOCV) results are presented. Different colors represent different Ameriflux/NEON study sites. The fraction of absorbed photosynthetically active radiation values used as model inputs for NEE estimates are directly extracted from MODIS.

The comparison of cumulative estimates of GPP and NEE using MODIS (**Table. C1**) and STARFM (**Table 2**) demonstrated generally comparable accuracy, with perennial and/or annual grass sites being predicted slightly better with MODIS fPAR, and grass-shrub mixture and grass-tree mixture sites being predicted with slightly higher accuracy using the STARFM fPAR inputs. Our results showed the importance of using STAFM inputs to better capture fine temporal resolution vegetation productivity, but the advantage of using STARFM for estimating cumulative C fluxes or vegetation growth is less significant.

**Table. C1** Modelperformance for estimating annual, seasonal, and monthly cumulative gross primary productivity (GPP) and net ecosystem exchange of CO2 (NEE) shown as coefficient of determination (R2), root mean square error (RMSE), and mean bias error (MBE) averaged from sites within different vegetation classes. The growing season is set from April to October. The fraction of absorbed photosynthetically active radiation (fPAR) values were directly extracted from MODIS.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Vegetation class | GPP | | | NEE | | |
| R2 | RMSE | MBE | R2 | RMSE | MBE |
| Annual cumulative fluxes (g C m-2 year-1) | | | | | | |
| Perennial and/or annual grass | 0.65 | 385.5 | 1.4 | 0.46 | 175.3 | 115.6 |
| Grass-shrub mixture | 0.66 | 240.5 | 34.4 | 0.53 | 106.6 | 89.0 |
| Grass-tree mixture | 0.70 | 409.3 | 98.2 | 0.35 | 175.5 | 79.3 |
| Growing season cumulative fluxes (g C m-2 per growing season) | | | | | | |
| Perennial and/or annual grass | 0.61 | 273.8 | 3.8 | 0.44 | 152.6 | 86.9 |
| Grass-shrub mixture | 0.67 | 167.8 | 28.1 | 0.60 | 94.3 | 72.8 |
| Grass-tree mixture | 0.54 | 324.3 | 96.2 | 0.31 | 128.1 | 35.4 |
| Monthly cumulative fluxes (g C m-2 month-1) | | | | | | |
| Perennial and/or annual grass | 0.72 | 48.6 | -1.6 | 0.46 | 32.8 | 9.8 |
| Grass-shrub mixture | 0.69 | 28.0 | 1.1 | 0.53 | 17.0 | 6.9 |
| Grass-tree mixture | 0.62 | 51.4 | 11.9 | 0.48 | 26.5 | 7.6 |

The comparison of spatial estimates of surface SOC stocks across NEON grassland sites showed that MODIS (**Fig. C3a**) and STARFM (**Fig. 6**) achieved very similar model performance, with higher model R2 obtained for using MODIS fPAR while lower RMSE obtained for using STARFM fPAR inputs. In general, the RCTM estimated higher SOC stocks compared to measurements taken at 0-30 cm depth, and lower SOC stocks compared to measurements taken at 0-100 cm depth (**Fig. C3**). The model fit was better for surface SOC modeling because model input dataset are mostly driven by surface C dynamics except for root zone soil moisture.

A graph of mathematical equations

Description automatically generated with medium confidence

**Figure. C3** The model performance for estimating soil organic carbon (SOC) stocks for NEON grassland sites using calibrated Rangeland Carbon Tracking and Monitoring (RCTM) system. In (a), the fraction of absorbed photosynthetically active radiation (fPAR) values are directly extracted from MODIS and the comparison is carried out against 0-30 cm field measurements of SOC stocks. In (b), the fPAR values are extracted from Spatial and Temporal Adaptive Reflectance Fusion Model (STARFM) estimates and the comparison is carried out against 0-100 cm field measurements of SOC stocks. In (c), the fPAR values are directly extracted from MODIS and the comparison is carried out against 0-100 cm field measurements of SOC stocks.

Appendix D: Model performance associated with the estimation of ecosystem respiration

A diagram of a field

Description automatically generated with medium confidence

**Figure. D1** The model performance for estimating ecosystem respiration (RECO) shown as coefficient of determination (R2), root mean square error (RMSE, C m-2 day-1), and mean bias error (MBE, C m-2 day-1) for different vegetation classes including (a) perennial and annual grass, (b) managed hay and pasture, (c) mixture of grass and shrub, and (d) mixture of grass and tree classes. Different colors represent different Ameriflux/NEON study sites.

**Table. D1** Modelperformance for estimating annual and monthly cumulative ecosystem respiration (RECO) shown as coefficient of determination (R2), root mean square error (RMSE), and mean bias error (MBE) averaged from sites within different vegetation classes.

|  |  |  |  |
| --- | --- | --- | --- |
| Vegetation class | R2 | RMSE | MBE |
| Annual cumulative fluxes (g C m-2 year-1) |  |  |  |
| Perennial and/or annual grass | 0.63 | 298.1 | 65.7 |
| Grass-shrub mixture | 0.63 | 149.5 | 65.0 |
| Grass-tree mixture | 0.69 | 246.7 | -40.4 |
| Monthly cumulative fluxes (g C m-2 month-1) |  |  |  |
| Perennial and/or annual grass | 0.73 | 35.6 | 3.8 |
| Grass-shrub mixture | 0.67 | 18.6 | 5.7 |
| Grass-tree mixture | 0.66 | 30.2 | -4.5 |

Appendix E: Simulated rangeland carbon fluxes grouped by study region

A screenshot of a graph

Description automatically generated

**Figure. E1** Model estimated temporal trends (2003-2022) in gross primary productivity (GPP), net ecosystem exchange (NEE), and surface soil organic carbon (SOC) stocks grouped by USDA agricultural regions including the Northern Great Plains (ND, SD, NE, KS), Southern Great Plains (TX, OK), Mountain states (MT, ID, WY, CO, UT, AZ, NM), Pacific states (WA, OR, CA), and Midwestern states (MN, WI, MI, IA, MO, IL, IN, OH). The solid lines represent mean values averaged from all sites within the group, while the lighter-colored lines with areas filled within represent standard deviations for GPP and NEE estimates. The red line shows zero baseline for NEE where a positive NEE denotes ecosystem carbon sink activity. Different scales were used for SOC due to differences in data ranges among regions.

Appendix F: Comparison of model performance using RCTM and L4C

We compared model performance for estimating daily GPP and NEE using RCTM and Soil Moisture Active-Passive (SMAP)’s Level 4 Carbon (L4C) product (Endsley et al., 2020). For convenience, a subset of the years (2015-2022) was selected for model comparison for perennial and/or annual grass, grass-shrub mixture, and grass-tree mixture sites. The comparison results are shown in **Table. E1** and **E2**, for GPP and NEE, respectively.

**Table. E1** Comparison of RCTM and L4C performance for estimating daily gross primary productivity (GPP) shown as coefficient of determination (R2), root mean square error (RMSE), and mean bias error (MBE).

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Vegetation class | R2 | | RMSE | | MBE | |
| RCTM | L4C | RCTM | L4C | RCTM | L4C |
| Perennial and/or annual grass | 0.57 | 0.57 | 2.51 | 2.68 | 0.06 | 0.69 |
| Grass-shrub mixture | 0.76 | 0.68 | 0.85 | 1.05 | 0.01 | 0.02 |
| Grass-tree mixture | 0.60 | 0.53 | 1.37 | 1.55 | 0.24 | 0.26 |

**Table. E2** Comparison of RCTM and L4C performance for estimating daily net ecosystem exchange (NEE) shown as coefficient of determination (R2), root mean square error (RMSE), and mean bias error (MBE).

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Vegetation class | R2 | | RMSE | | MBE | |
| RCTM | L4C | RCTM | L4C | RCTM | L4C |
| Perennial and/or annual grass | 0.30 | 0.16 | 1.59 | 1.94 | 0.30 | 0.26 |
| Grass-shrub mixture | 0.55 | 0.43 | 0.65 | 0.74 | 0.11 | 0.16 |
| Grass-tree mixture | 0.38 | 0.39 | 1.03 | 1.01 | 0.25 | 0.21 |

Our comparison results in **Table. E1** showed that RCTM outperformed L4C for estimating daily GPP from the grass-shrub mixture and grass-tree mixture sites. While model fit represented by R2 was similar between the two models for estimations at perennial and/or annual grass sites, the modeling bias was lower using RCTM. The results in **Table. E2** demonstrated better model performance for estimating daily NEE using RCTM compared to L4C for both perennial and/or annual grass and grass-shrub mixture sites. Slightly better model accuracy was observed for grass-tree mixture sites using the L4C model, suggesting the need to further improve RCTM-based modeling of C fluxes from sites with a significant presence of tree. The comparison results support the notion that model parameterization tailored to the specific rangeland region of application is necessary for enhancing model accuracy.

Appendix G: Climate drivers for temporal patterns delineated with remote sensing imagery

A group of graphs with numbers

Description automatically generated with medium confidence

**Figure. G1** Temporal trends (2003-2022) of mean annual temperature (AT), annual precipitation (ppt), and fraction of absorbed photosynthetically active radiation (fPAR) grouped by plant functional types and USDA agricultural regions including the Northern Great Plains (ND, SD, NE, KS), Southern Great Plains (TX, OK), Mountain states (MT, ID, WY, CO, UT, AZ, NM, NV), Pacific states (WA, OR, CA), and Midwestern states (MN, WI, MI, IA, MO, IL, IN, OH). The red lines represent mean values averaged from each year for fPAR. Pearson correlation between annual average fPAR and both AT and ppt are presented as Corr R values with significant correlations at P < 0.05 labeled with \*. Different scales were used due to differences in data ranges among regions.

REFERENCES

Endsley, A. K., Kimball, J. S., Reichle, R. H., & Watts, J. D. (2020). Satellite monitoring of global surface soil organic carbon dynamics using the SMAP Level 4 carbon product. Journal of Geophysical Research: Biogeosciences, 125(12), e2020JG006100. https://doi.org/10.1029/2020JG006100

Gao, F., Masek, J., Schwaller, M., & Hall, F. (2006). On the blending of the landsat and MODIS surface reflectance: Predicting daily landsat surface reflectance. IEEE Transactions on Geoscience and Remote Sensing, 44(8), 2207–2218. https://doi.org/10.1109/TGRS.2006.872081

Hartig, F., Minunno, F., Paul, S., Cameron, D., Tankred, O., & Maximilian, P. (2023). BayesianTools: General-purpose MCMC and SMC samplers and tools for bayesian statistics. Retrieved November 7, 2023, from https://cran.r-project.org/web/packages/BayesianTools/index.html

Kovalskyy, V., & Roy, D. P. (2013). The global availability of Landsat 5 TM and Landsat 7 ETM+ land surface observations and implications for global 30m Landsat data product generation. Remote Sensing of Environment, 130, 280–293. https://doi.org/10.1016/j.rse.2012.12.003

Myneni, R., Knyazikhin, Y., & Park, T. (2021). MODIS/Terra Leaf Area Index/FPAR 8-Day L4 Global 500m SIN Grid V061. https://doi.org/10.5067/MODIS/MCD15A3H.061

Ramcharan, A., Hengl, T., Nauman, T., Brungard, C., Waltman, S., Wills, S., & Thompson, J. (2018). Soil property and class maps of the conterminous United States at 100-meter spatial resolution. Soil Science Society of America Journal, 82(1), 186–201. https://doi.org/10.2136/sssaj2017.04.0122

Roy, D. P., Wulder, M. A., Loveland, T. R., C.E., W., Allen, R. G., Anderson, M. C., et al. (2014). Landsat-8: Science and product vision for terrestrial global change research. Remote Sensing of Environment, 145, 154–172. https://doi.org/10.1016/j.rse.2014.02.001

Schaaf, C., & Wang, Z. (2015). MODIS/Terra and Aqua Nadir BRDF-Adjusted Reflectance Daily L3 Global 500 m SIN Grid V006. https://doi.org/10.5067/MODIS/MCD43A4.061

Thornton, M. M., Thornton, P. E., Wei, Y., Mayer, B. W., Cook, R. B., & Vose, R. S. (2022). Daymet: Monthly climate summaries on a 1-km grid for North America, version 4 R1. Oak Ridge National Laboratory. Oak Ridge, Tennessee, USA. https://doi.org/10.3334/ORNLDAAC/2131

Watts, J. D., Powell, S. L., Lawrence, R. L., & Hilker, T. (2011). Improved classification of conservation tillage adoption using high temporal and synthetic satellite imagery. Remote Sensing of Environment, 115(1), 66–75. https://doi.org/10.1016/j.rse.2010.08.005

Williams, D. L., Goward, S., & Arvidson, T. (2006). Landsat: Yesterday, today, and tomorrow. Photogrammetric Engineering and Remote Sensing, 72(10), 1171–1178. https://doi.org/10.14358/PERS.72.10.1171

Xia, Y., Mitchell, K., Ek, M., Sheffield, J., Cosgrove, B., Wood, E., et al. (2012). NLDAS Noah Land Surface Model L4 Hourly 0.125 x 0.125 degree V002. Retrieved November 7, 2022, from https://disc.gsfc.nasa.gov/datasets/NLDAS\_NOAH0125\_H\_002/summary