

Carbon Sequestration in Forests: Current Rates and Attribution

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Funding: NASA NNH05ZDA001N-NACP, NASA Carbon Monitoring System



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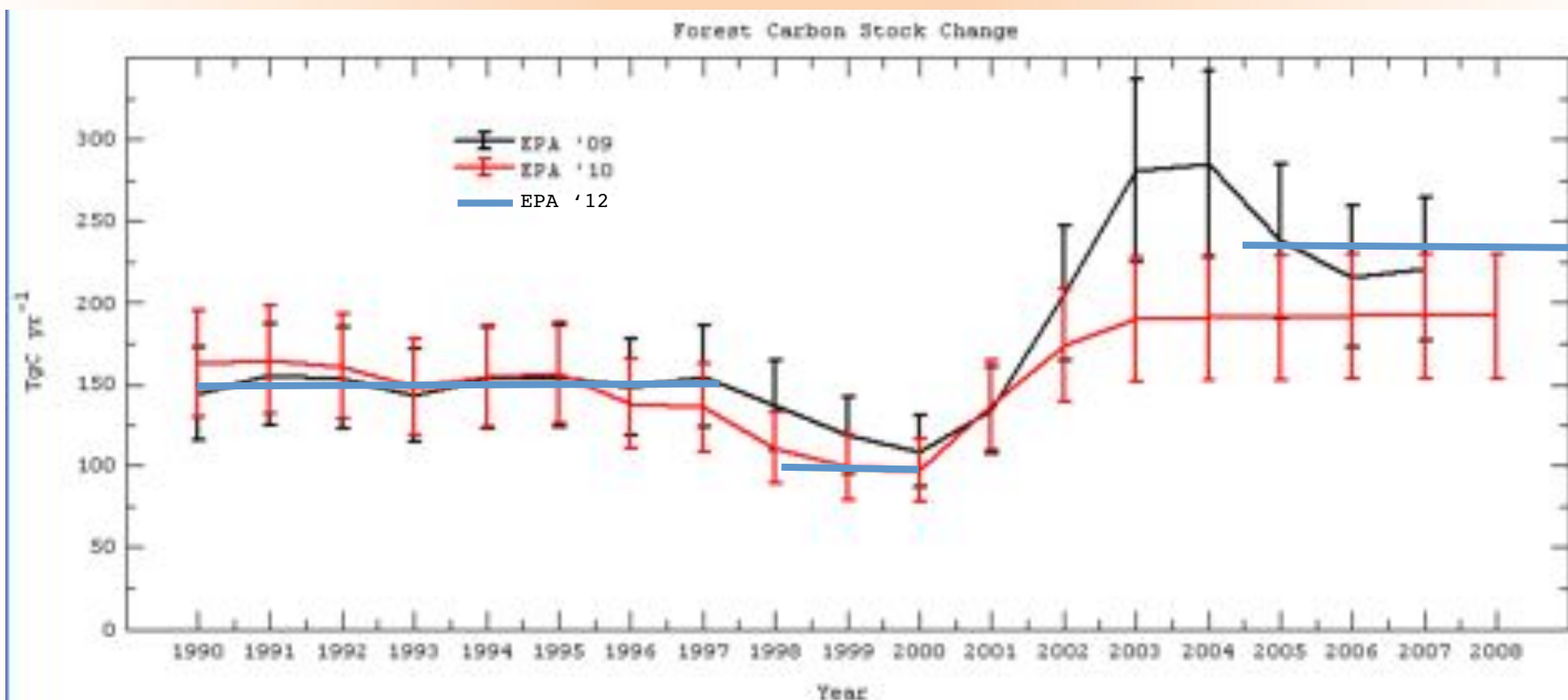
US Report to the UNFCCC Annual Inventory of Greenhouse Gas Emissions and Sinks

In 2010:

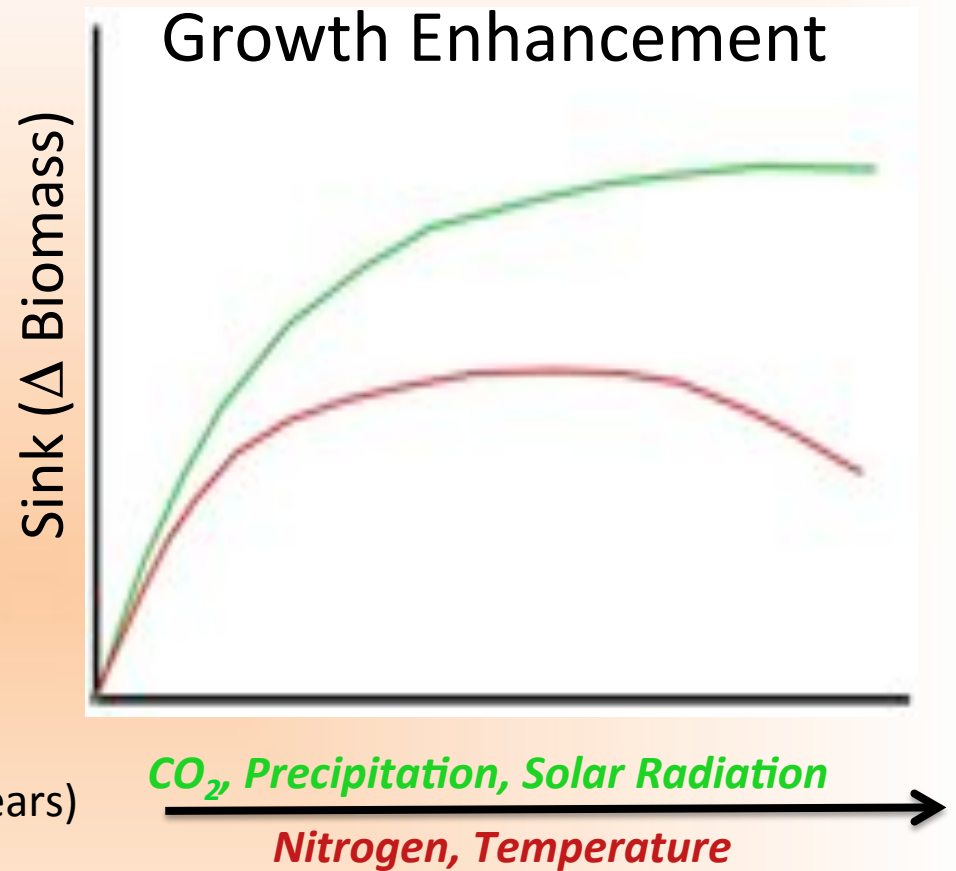
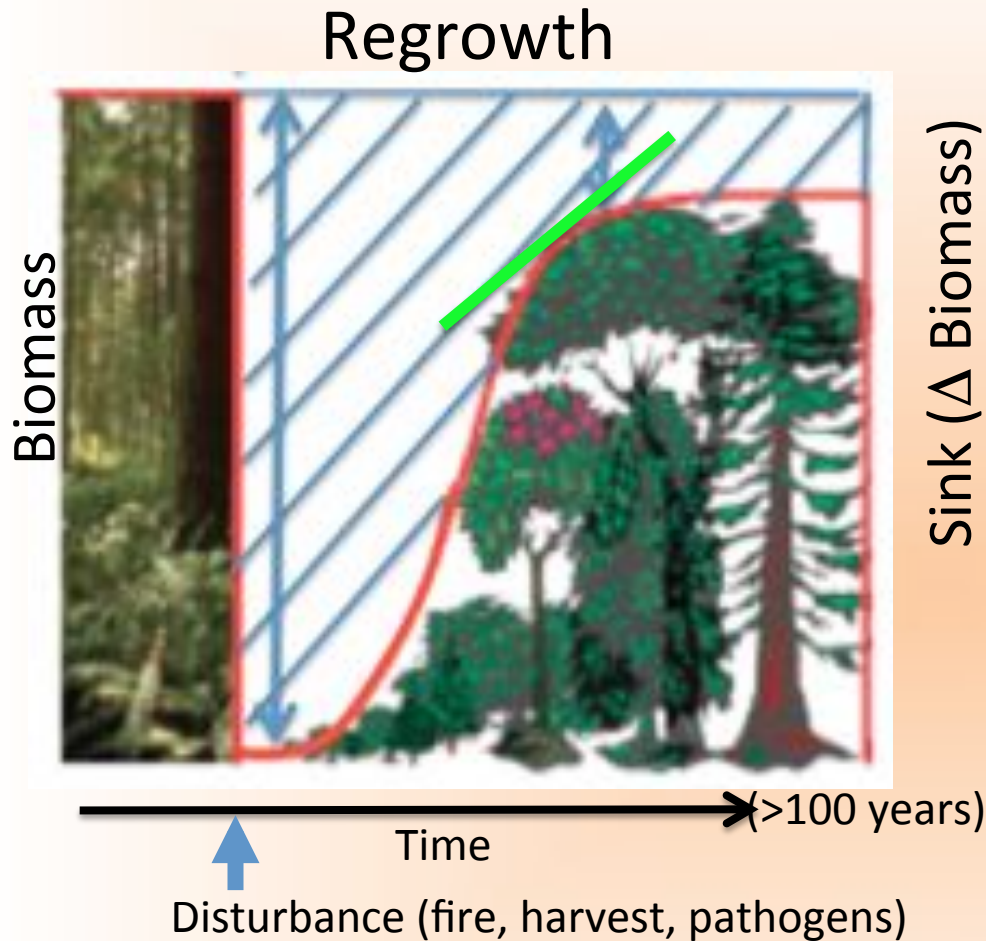
US emissions from fossil fuels: 1,556 Tg C

US forest sink: 251 +/- 80 Tg C or 16% of fossil fuel emissions

Forest sink estimate from FIA (periodic sampling of >150,000 plots) **“The Gold Standard”**



Reasons why a forests would be carbon sinks



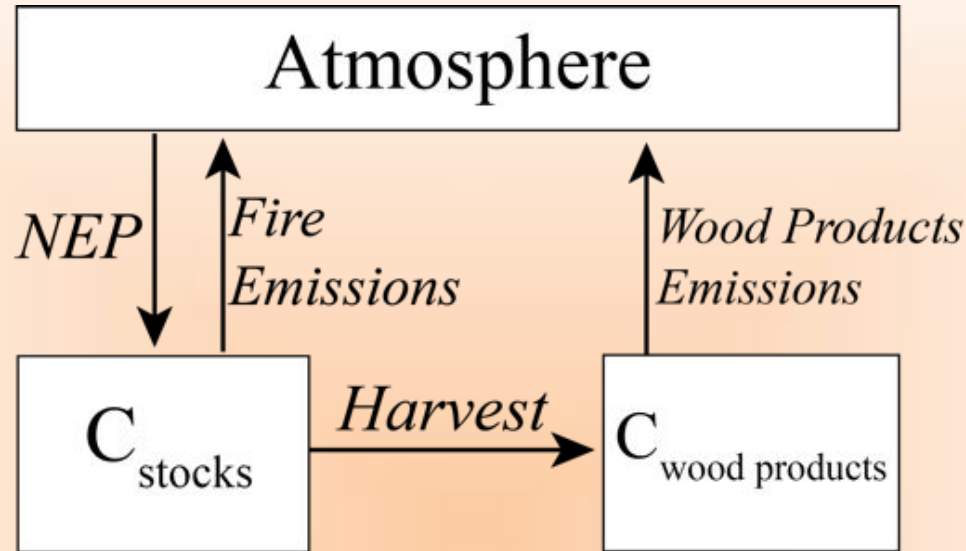
$$NEP = NPP - RH \quad (= GPP - RE)$$

***Regrowth sink: reduced carbon pools

Enhancement: increasing NPP

Other processes less understood: decreases in mortality, respiration attenuation

Forest Sector Carbon Exchanges



Translate ΔC_{stocks} into *NEP* to diagnose regrowth vs enhancement

$$NEP_{stock\ change} = \Delta C_{stocks} + Harvest + Fire\ Emissions$$

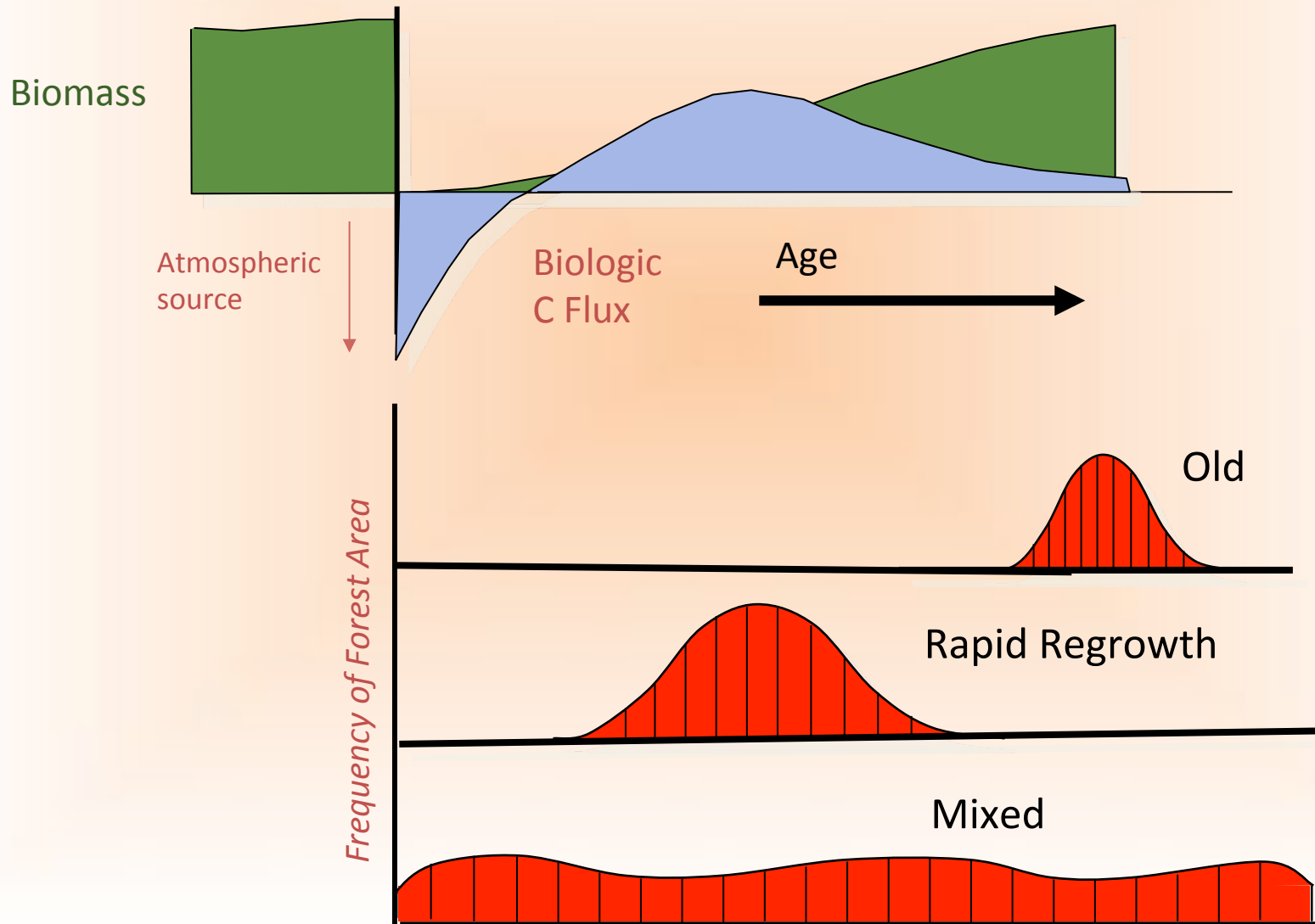
Includes all effects including age and enhancement

$$NEP_{regrowth} = NPP - RH$$

Model accounts for age only (same as Canadian approach for UNFCCC Reporting)

Our Approach:

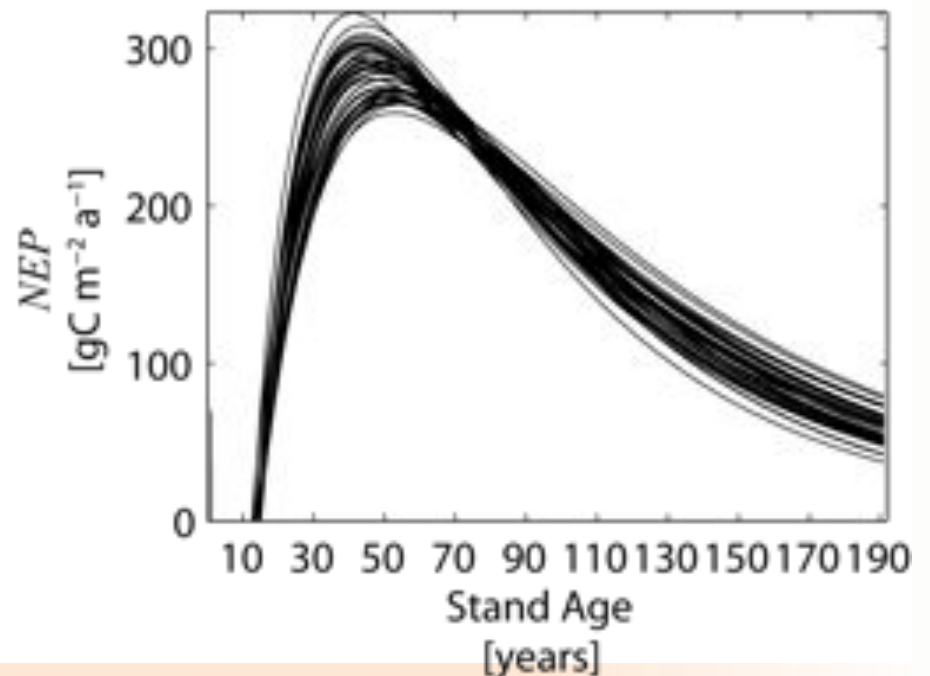
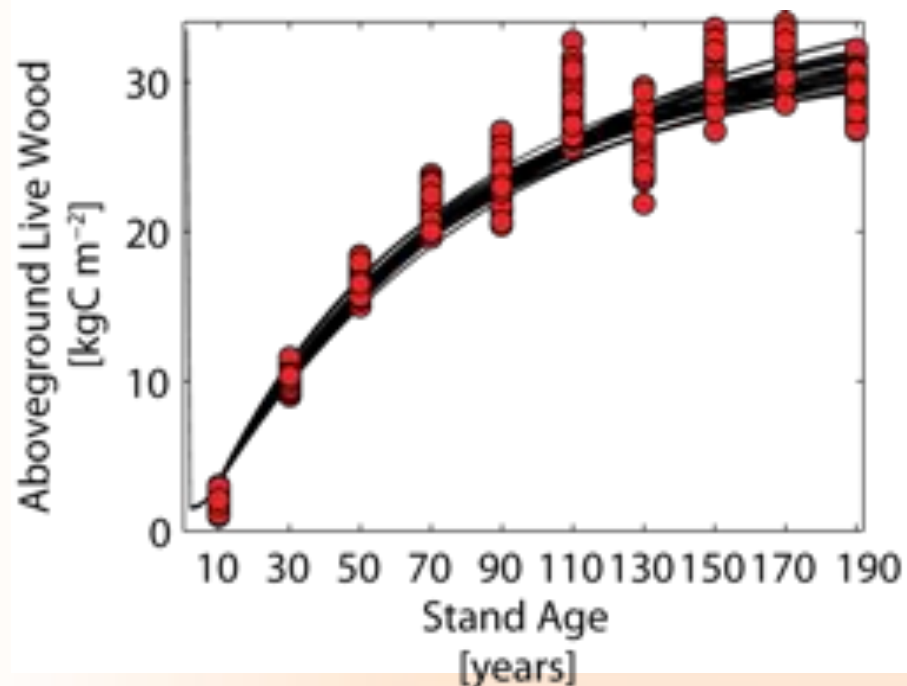
- Calibrate CASA with FIA Forest Age-Biomass data specific to forest type, productivity level and region
- Develop a spatially explicit map of forest age for CONUS (from FIA and Landsat based VCT, Goward et al)
- Assign carbon fluxes based on age of forest





Flux Trajectories

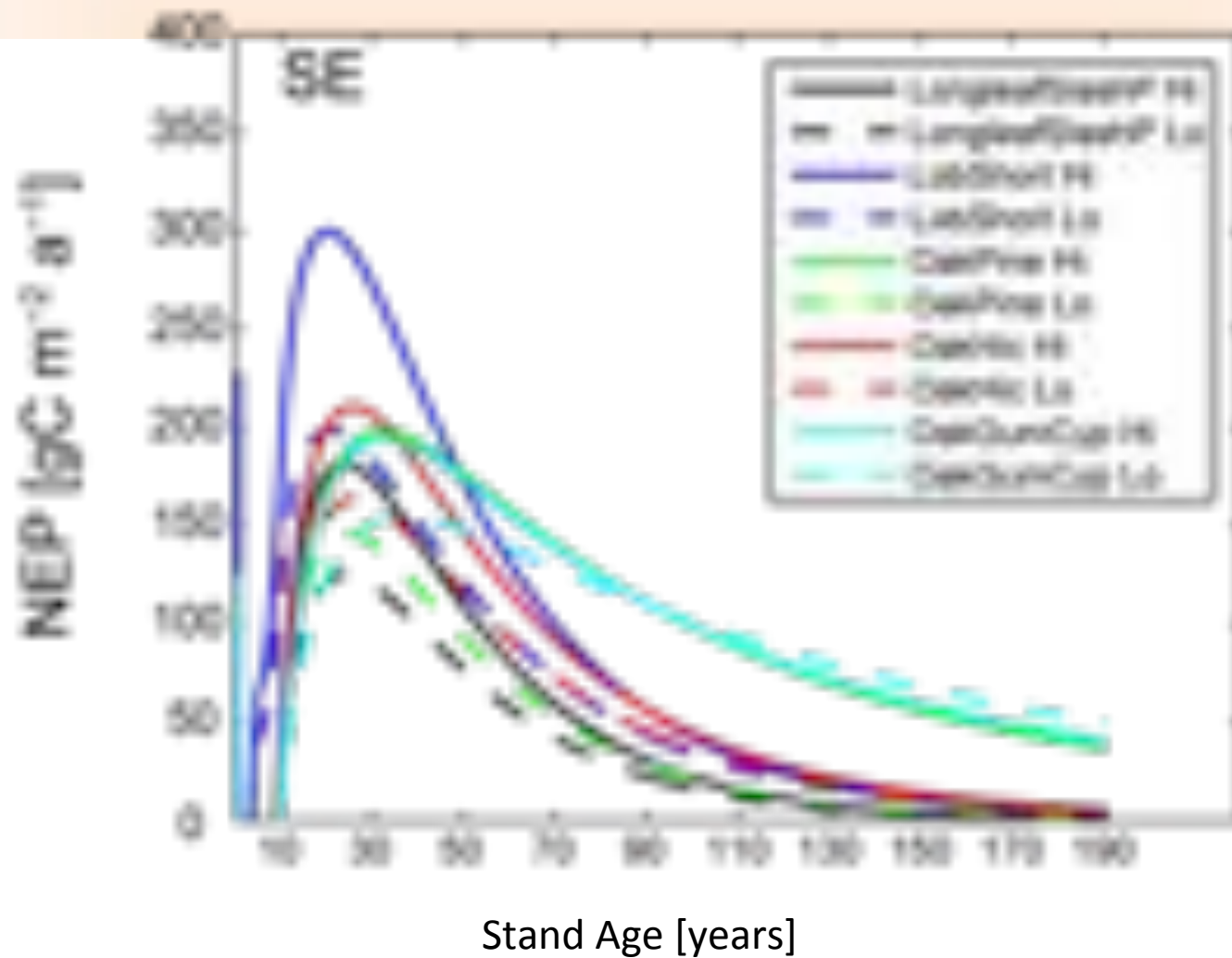
Unique trajectories for regional forest types, productivity classes, and climate settings



Uncertainty formally analyzed with Monte Carlo fitting
biomass sampling error from FIA (+/- 10 to 100%)
volume to carbon conversion (+/- 7%)

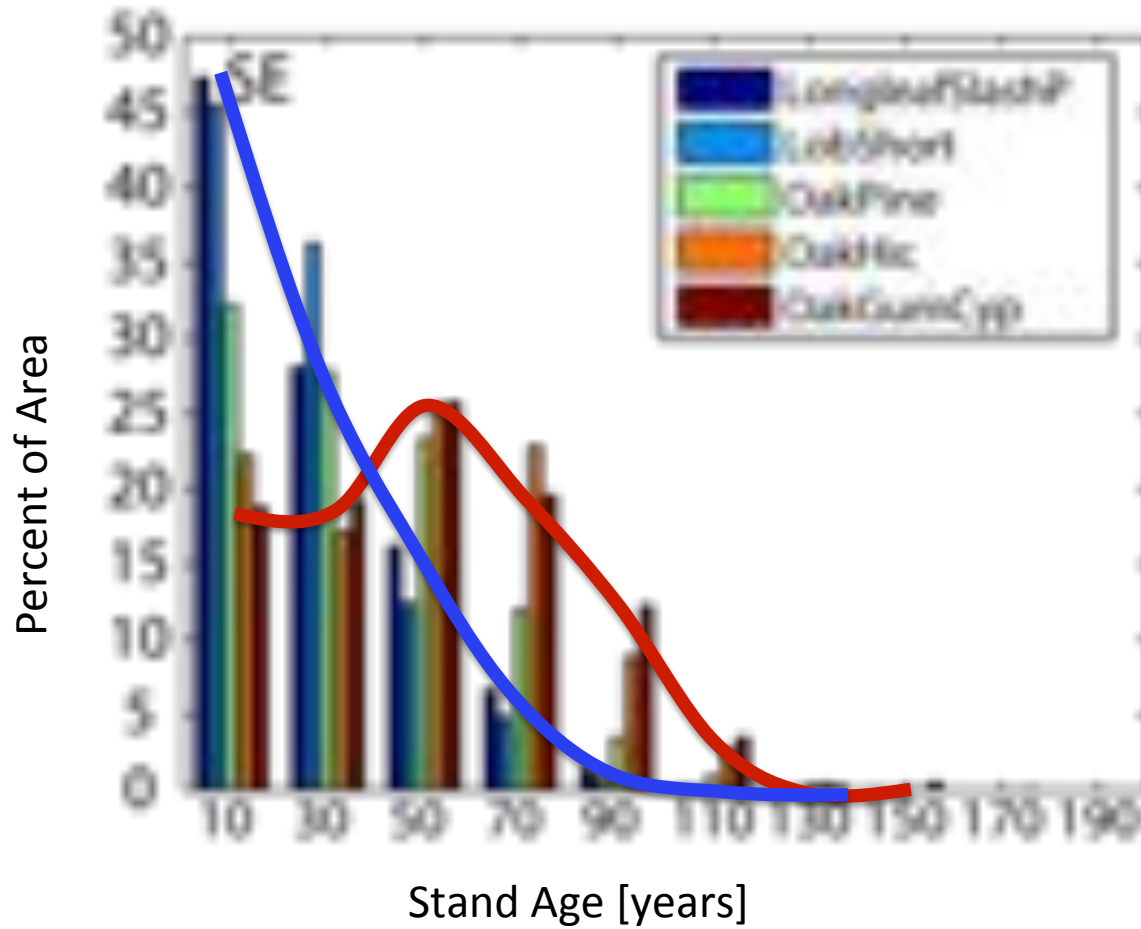


Flux Trajectories Within Regions



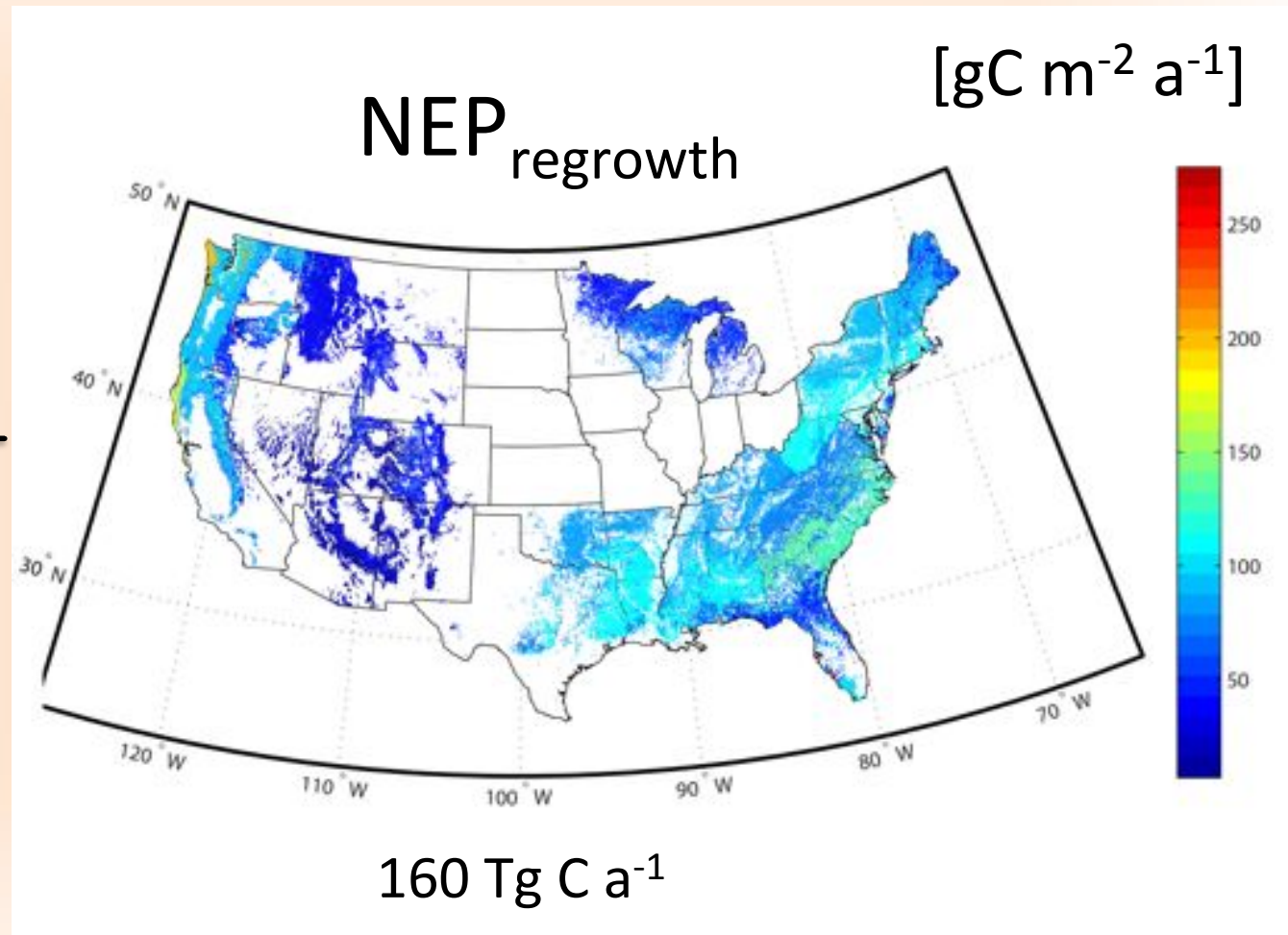
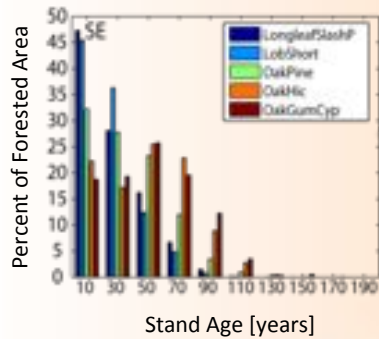
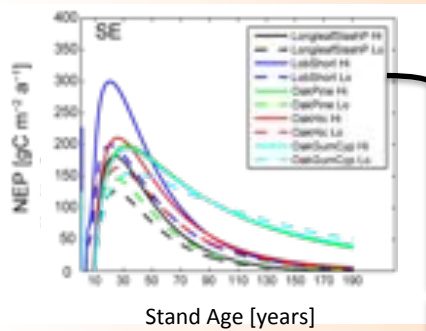


Age Structures Within Regions

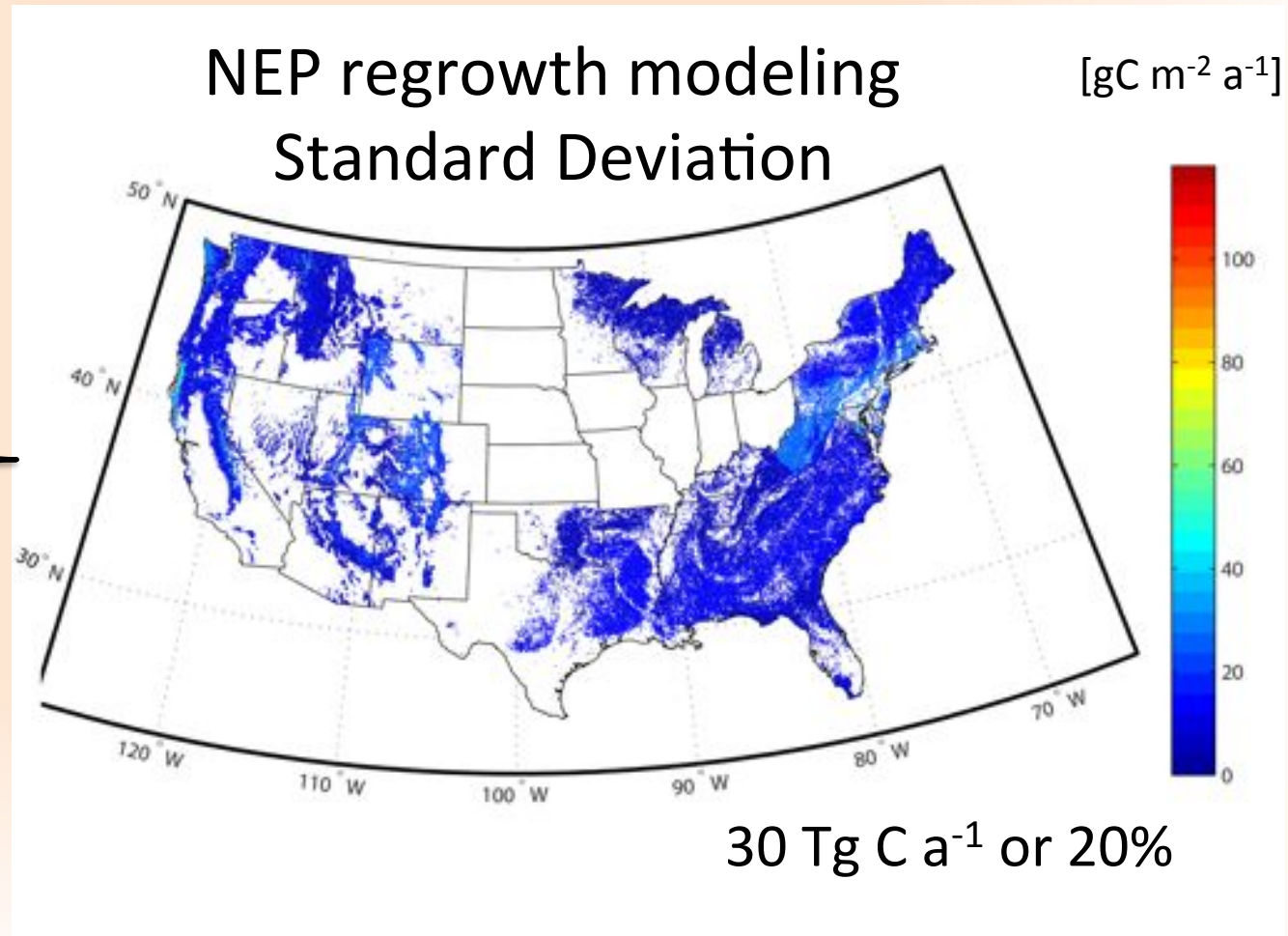
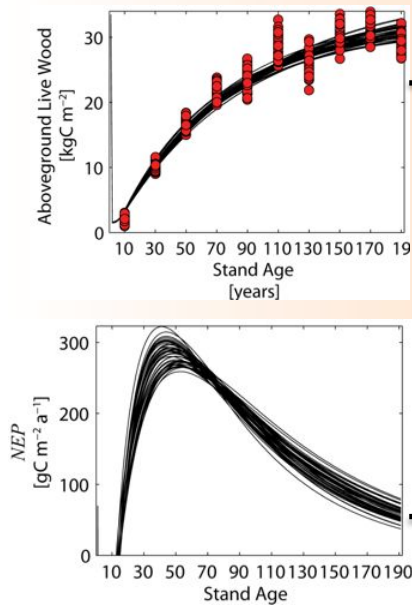




Regrowth Uptake



Regrowth Uptake Uncertainty

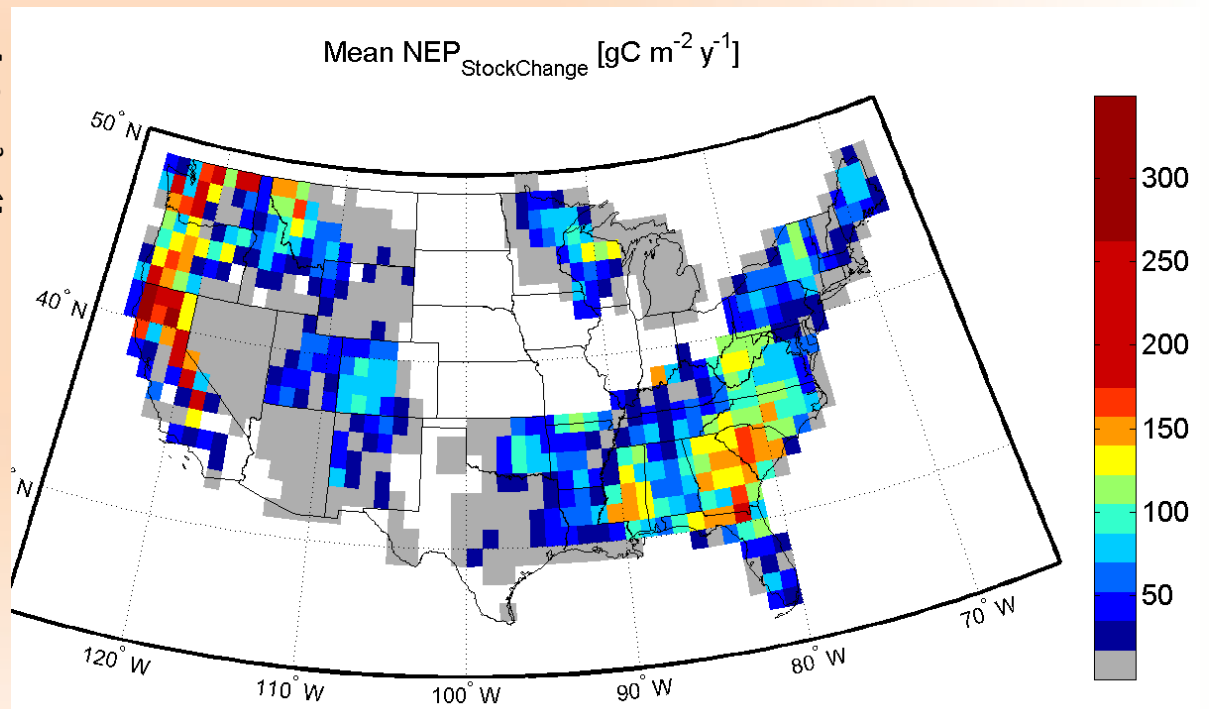
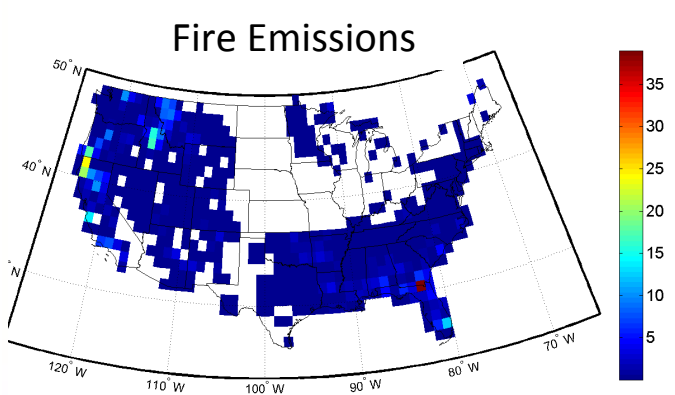
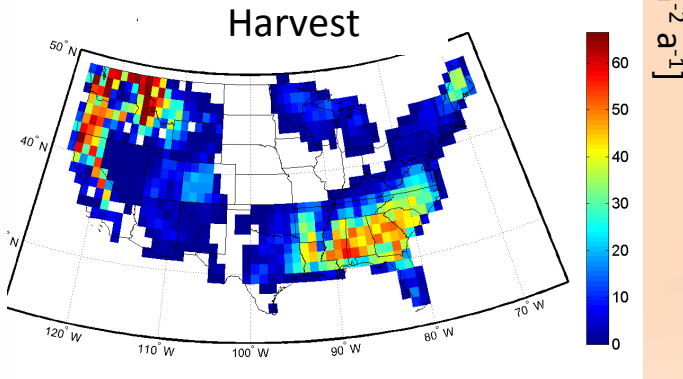
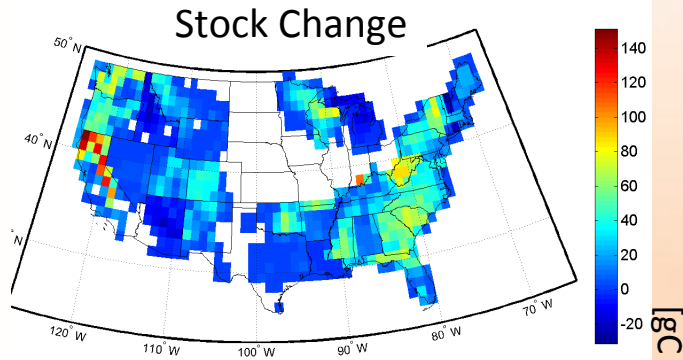




NEP from Stock Changes

NEP_{stock change}

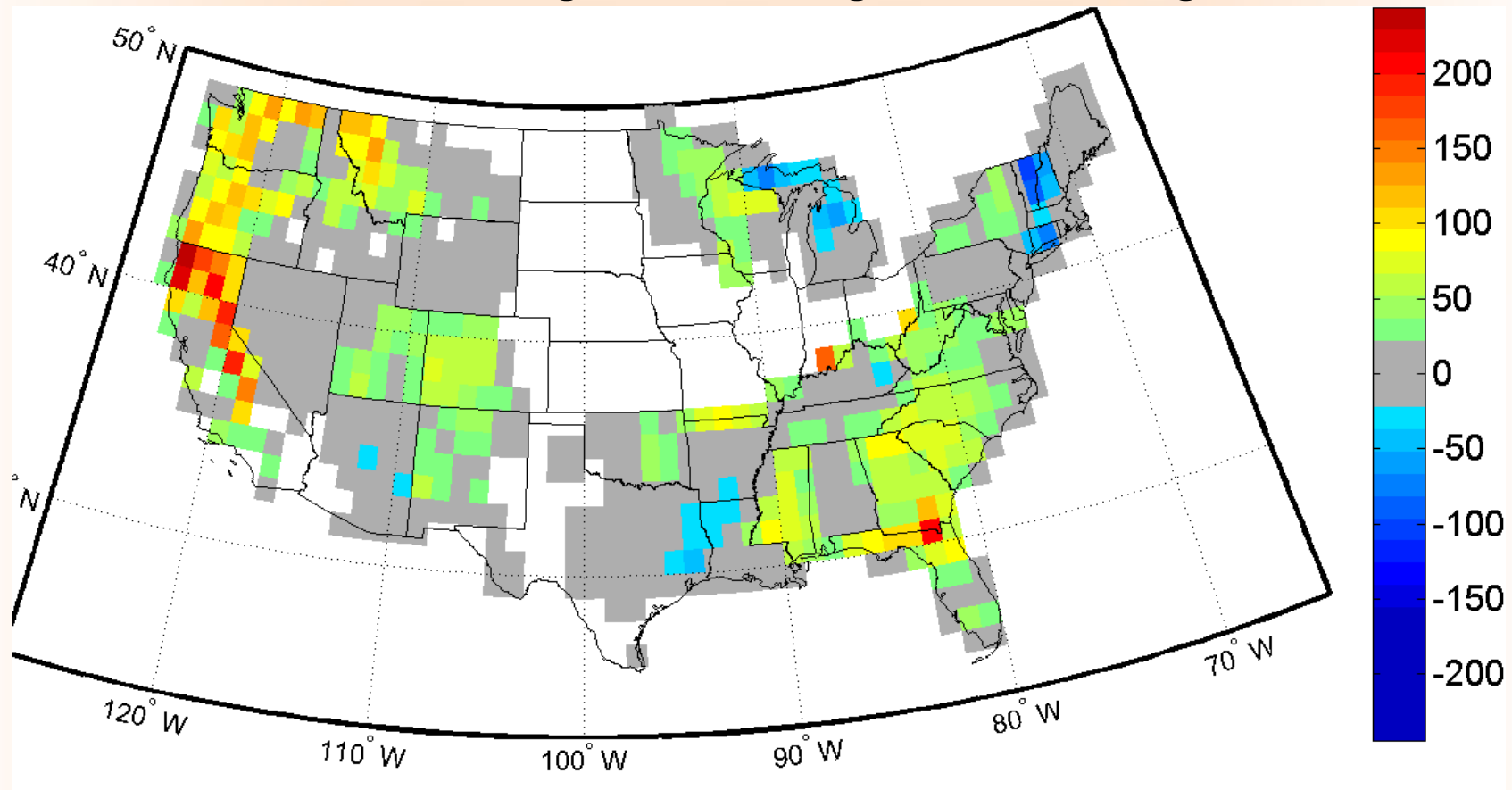
$$\text{NEP}_{\text{stock change}} = \Delta\text{Forest Stock} + \text{Harvest Flux} + \text{Fire Flux}$$



310 Tg C a⁻¹

Why are they so different?

$NEP_{\text{stock change}} - NEP_{\text{regrowth modeling}}$

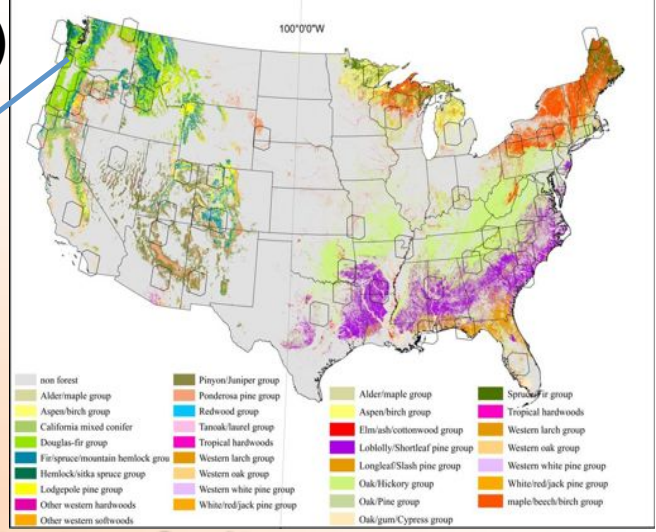


$$310 - 160 = 150 \text{ Tg C a}^{-1}$$

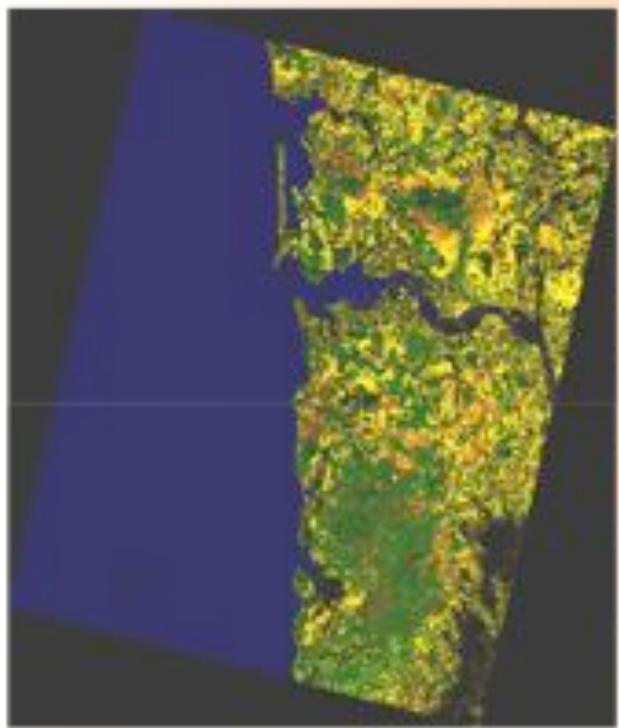
Stock Change NEP is 2 X larger than Regrowth sink

[gC m⁻² a⁻¹]

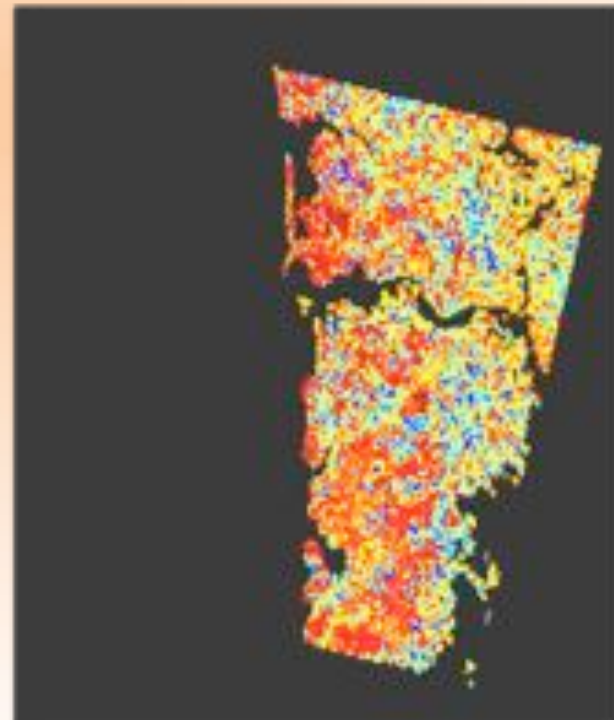
What does the Landsat VCT disturbance history (Goward et al.) tell us about forest age and regrowth?



Year of Disturbance



Forest NEP [gC m⁻² a⁻¹]



sinks +
sources -

■ generate detailed maps of forest NEP, Biomass, etc.

Age Structure of Forests Estimated Using Landsat VCT 1985-2005, FIA < 1985

Introducing fine scale disturbance data reduced the estimated CONUS NEP

Higher disturbance rates especially in regions with large forest industry produce younger forests with lower NEP

***Makes the discrepancy between Stock Change NEP and Regrowth NEP larger
Stock Change NEP 2.6 X larger than Regrowth NEP**

Region	AREA (1e9m ²)	NEP RS (TgC/yr)	SE (TgC/yr)	NEP FIA (TgC/yr)	SE (TgC/yr)	NPP RS (TgC/yr)	NPP FIA (TgC/yr)	Wood RS (TgC)	Wood FIA (TgC)	<25yr RS %	<25yr FIA %	<5yr RS %	<5yr FIA %	
NLS	212	10	1.29	12	1.29	85	88	706	851	23	16	4	3	0.95
NPS	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SE	355	22	3.47	30	3.47	308	317	1700	1939	51	39	12	8	2.27
SC	420	28	4.27	40	4.27	316	347	1948	2300	45	37	10	8	1.96
RMN	192	4	1.81	7	1.81	65	73	762	914	34	21	8	5	1.55
RMS	493	10	5.51	11	5.51	87	88	1265	1372	26	1	7	0	1.2
PSW	127	8	2.81	13	2.81	89	97	834	1236	28	11	9	2	1.29
PNW	202	10	2.93	18	2.93	167	171	1483	1788	45	19	8	4	1.9
Total	2339	120	27.88	164	27.88	1377	1451	11094	13015	30	17	7	4	1.34

East

1.46721854
3

West

1.416992
11

Sensitivity Analyses

Errors in the representation of biomass accumulation with stand age could cause large errors in estimated fluxes

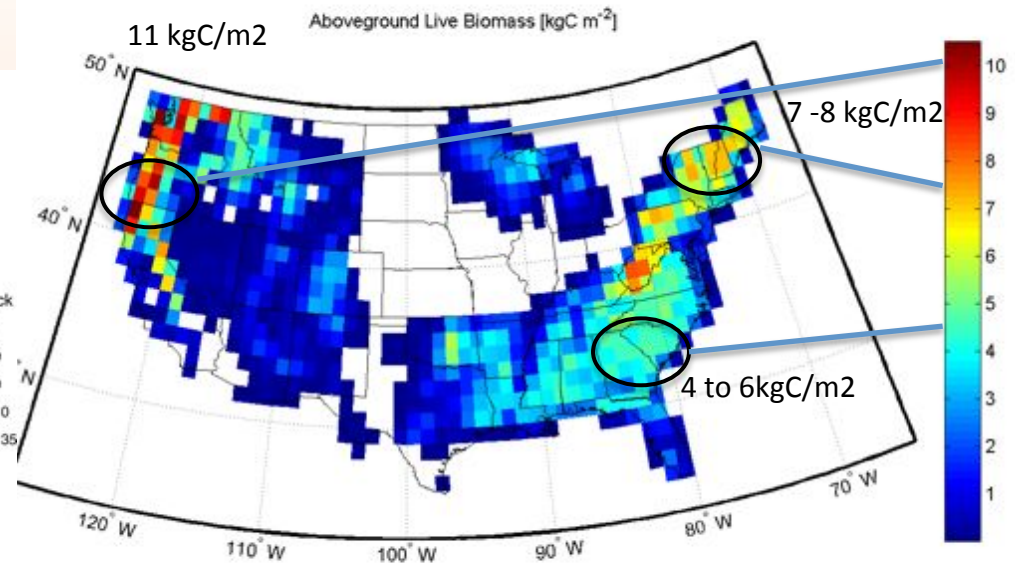
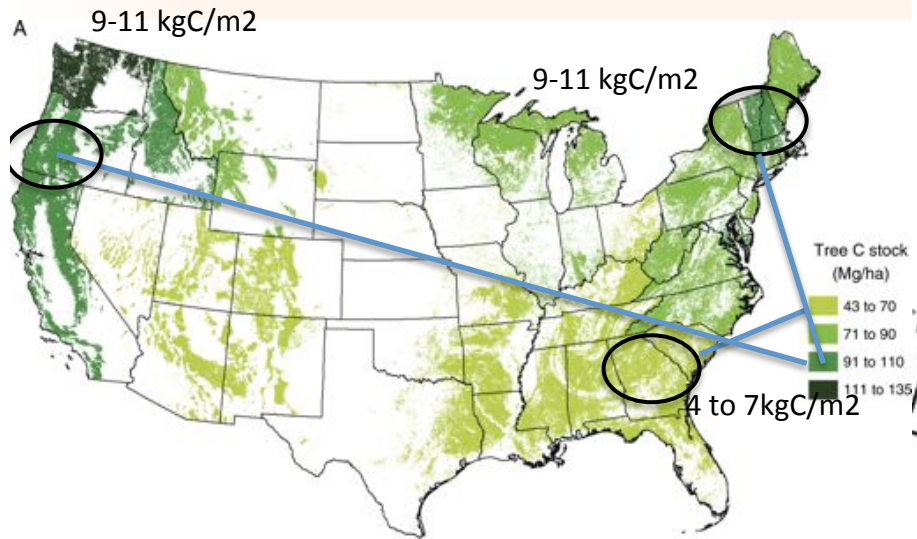
- 1) wood turnover has a large influence on rate of biomass increase and is poorly constrained
- 2) stand thinning (selective logging) may lower biomass in the inventory without resetting age

3) age reporting may be biased

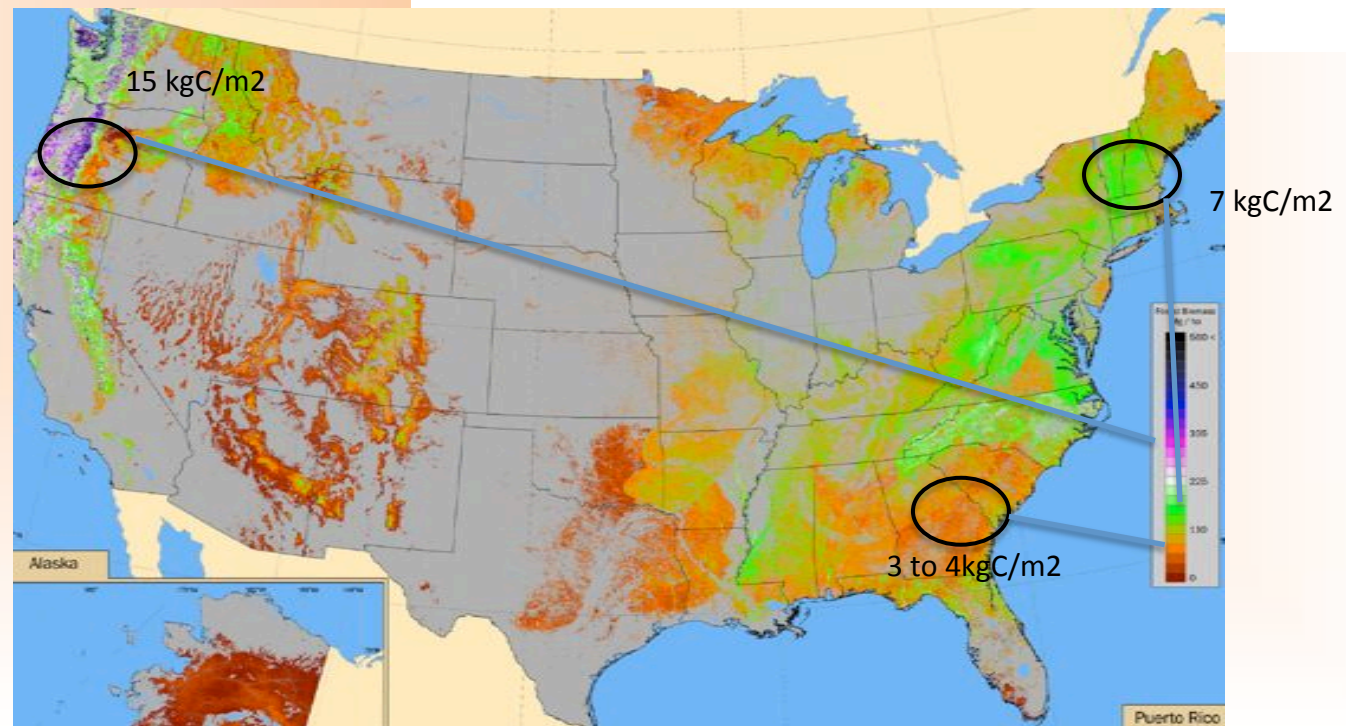
	<i>NEP</i> [Tg C a ⁻¹]	<i>NPP</i> [Tg C a ⁻¹]	<i>AGB</i> [Pg C]
Original Results	164 (28)	1451	13.0
Wood Turnover Increased 10%	169 (30)	1714	13.2
Biomass Increased 10%	187 (32)	1761	14.2
Stand Age -5 years	173 (30)	1860	13.7
Stand Age +5 years	162 (33)	1401	12.3

Biomass would have to be 70% higher to produce the $NEP_{stock\ change}$

McKinley et al '11 from Woodbury



Blackard et al '08 Above ground dry weight biomass



Recent Studies presenting Evidence of Growth Enhancement

Methods Employed: Inventory, Modeling, Eddy Covariance, Tree Ring

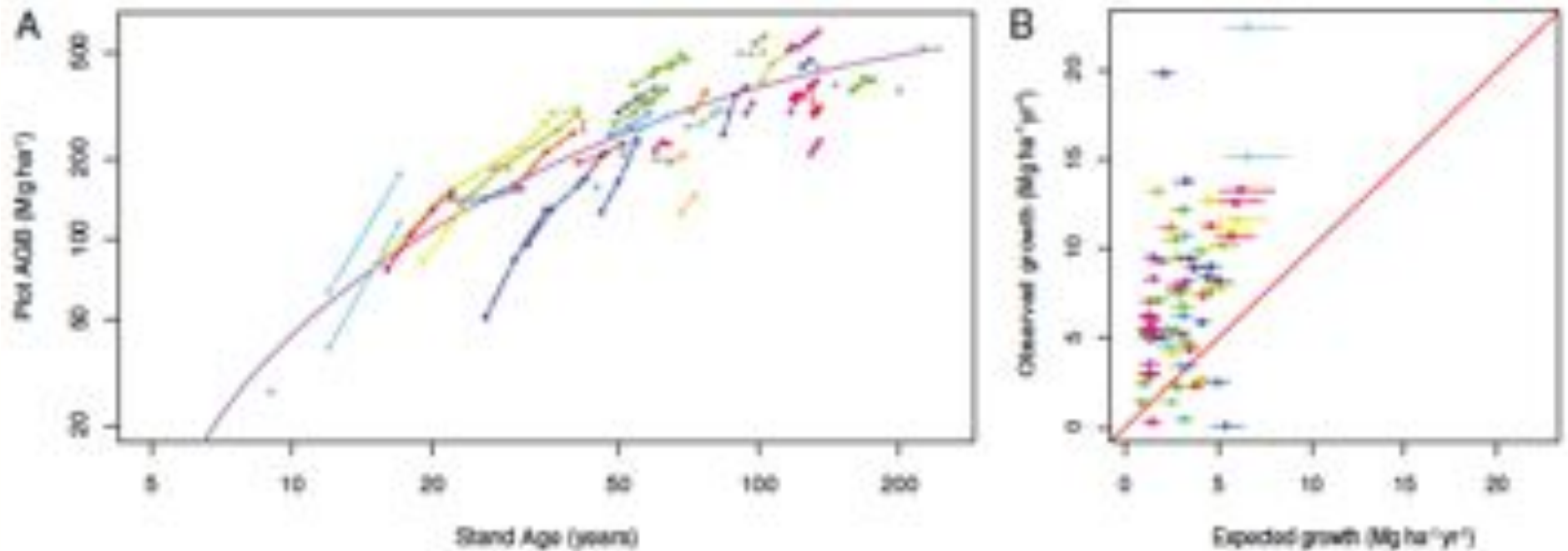
Source	Region	<i>NPP</i>	<i>NEP_c</i>	ΔNPP	$\Delta NPP\%$	ΔNEP	Approaches †	Factors‡
Thomas et al. 2010	US northeast	650	11	0.37	0.1%	<i>0.09</i>	ΔAGB , 1	N
Houghton et al. 2003	Global land	400	13	<i>0.43</i>	<i>0.1%</i>	<i>0.11</i>	Budget, 1	all
Bellassen et al. 2011	Europe	604	<i>30</i>	1.00	0.2%	0.87	Model, 1	CO ₂ , C
Beta Factor 50%	--	650	<i>35</i>	1.16	0.2%	<i>0.29</i>	Model, 1	CO ₂
Zaehle et al. 2006	Europe	750	33	<i>1.10</i>	<i>0.3%</i>	<i>0.28</i>	Model+, 1	CO ₂ , C
Pan et al. 2009	US Mid-Atlantic	765	83	2.25	0.3%	0.83	Model, --	CO ₂ , C, N, O ₃
Williams et al. 2011	US	744	81	<i>2.70</i>	<i>0.6%</i>	<i>0.68</i>	Model+, 1	all
Desai et al. 2007	US Wisconsin	402	100	<i>3.30</i>	<i>0.8%</i>	<i>0.83</i>	Model, 1	CO ₂ , C
Cole et al. 2010	US West	--	--	--	1.1%	--	ΔAGB , --	all
McMahon et al. 2010	Global SERC Plots	808	808	<i>27.00</i>	<i>3.3%</i>	<i>6.79</i>	ΔAGB , 1	all
Pilegaard et al. 2011	Denmark	864	<i>79</i>	<i>36.00</i>	<i>4.2%</i>	23.00	EC, 2	all
Urbanski et al. 2007	US Massachusetts	650	<i>125</i>	<i>30.00</i>	<i>4.6%</i>	13.00	EC, 2	all
Dragoni et al. 2010	US Indiana	650	<i>175</i>	<i>32.00</i>	<i>4.9%</i>	10.00	EC, 2	all
Average		661	130	11.4	1.58%	4.7		
Median		650	80	2.5	0.62%	0.8		

$\text{gC m}^{-2} \text{y}^{-1}$



Plots Show Accelerated Growth

Present-day growth rates exceed those expected from chronosequences of biomass regrowth with forest age



McMahon et al (2010) PNAS

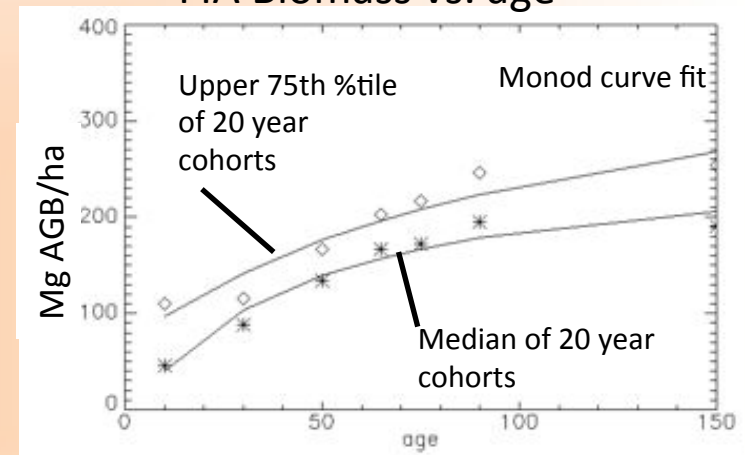
Analysis of individual FIA Plot data for Eastern US Forests (>1000 Plots in Each State)

Construct age dependent biomass trajectories for major forest types (Regrowth)

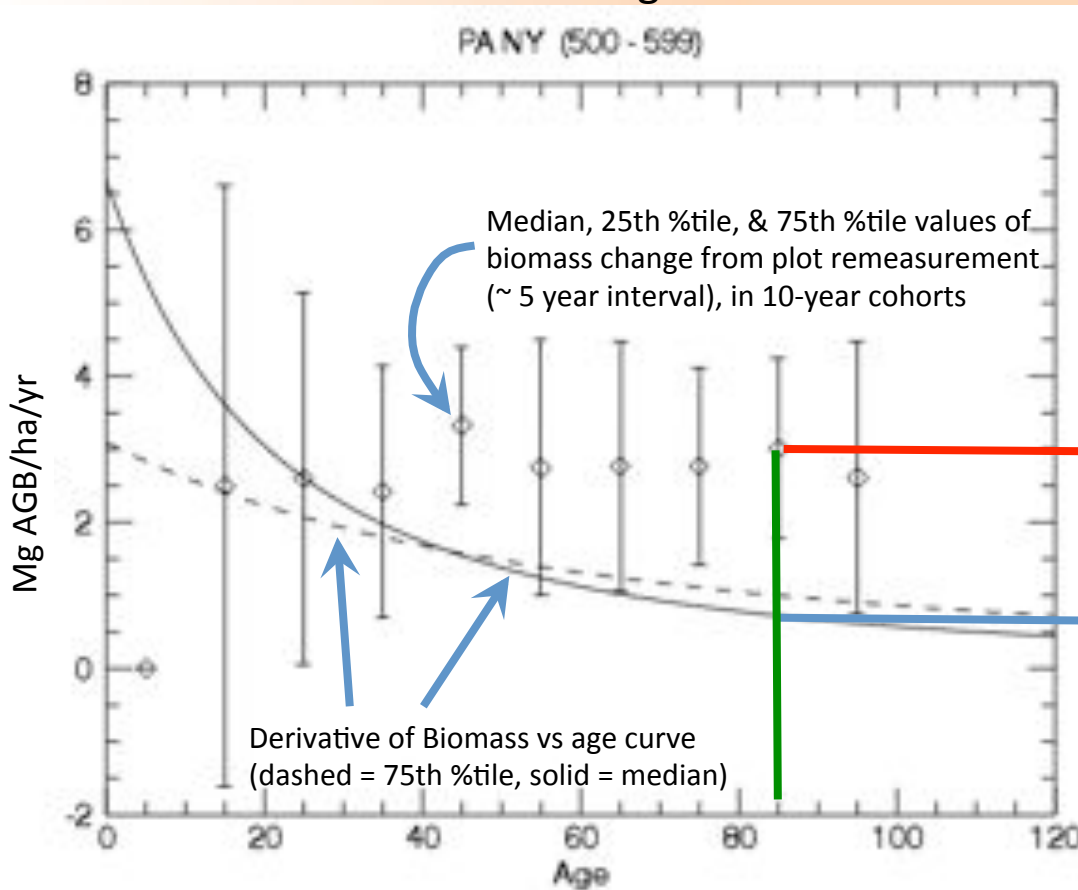
Estimate the change in biomass of individual plots between the 2 most recent inventories (Stock Change)



FIA Biomass vs. age



Biomass change rate



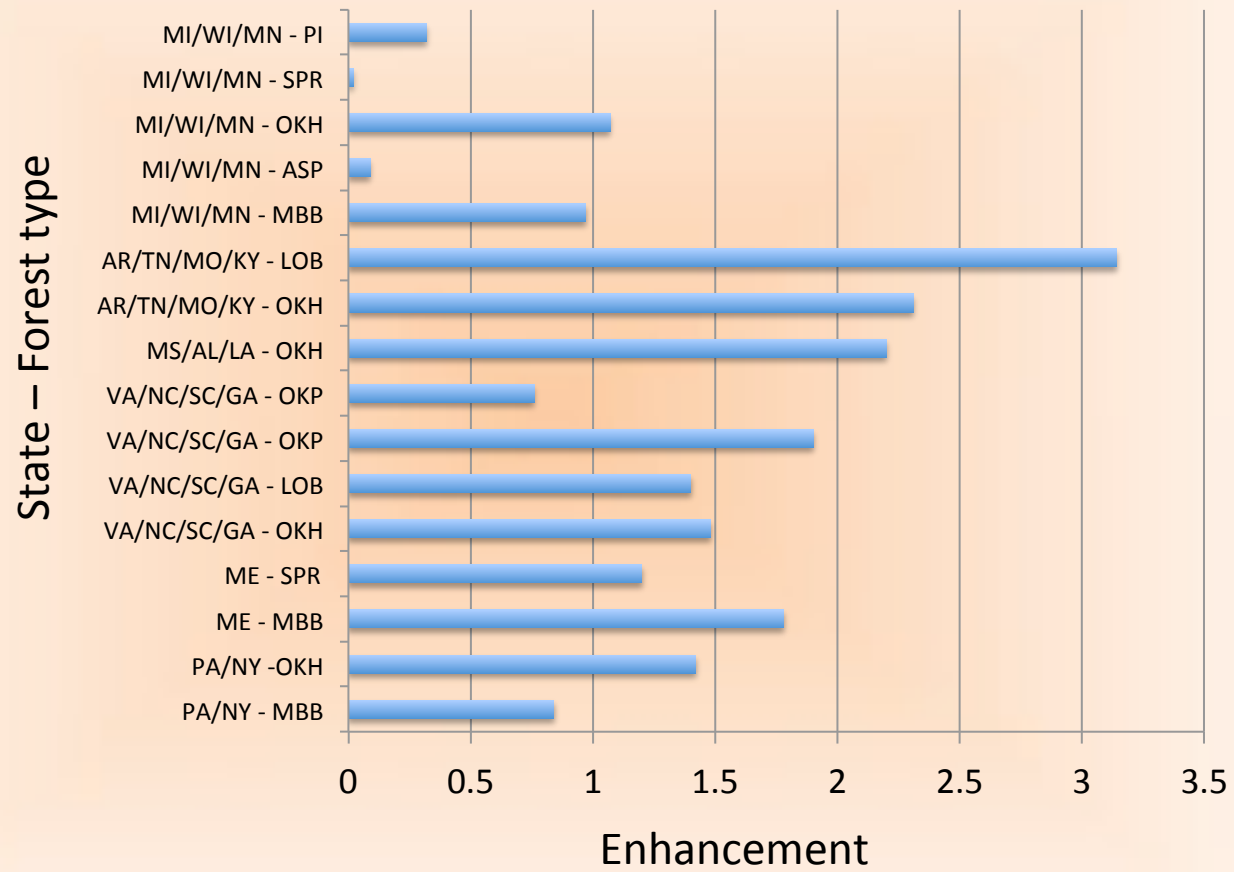
85 year old forests

Stock Change = 3 MgC/ha/yr (300 gC/m²/yr)

Regrowth = 0.7

$$\text{Enhancement} = \frac{3.0 - 0.7}{0.7} = 2$$

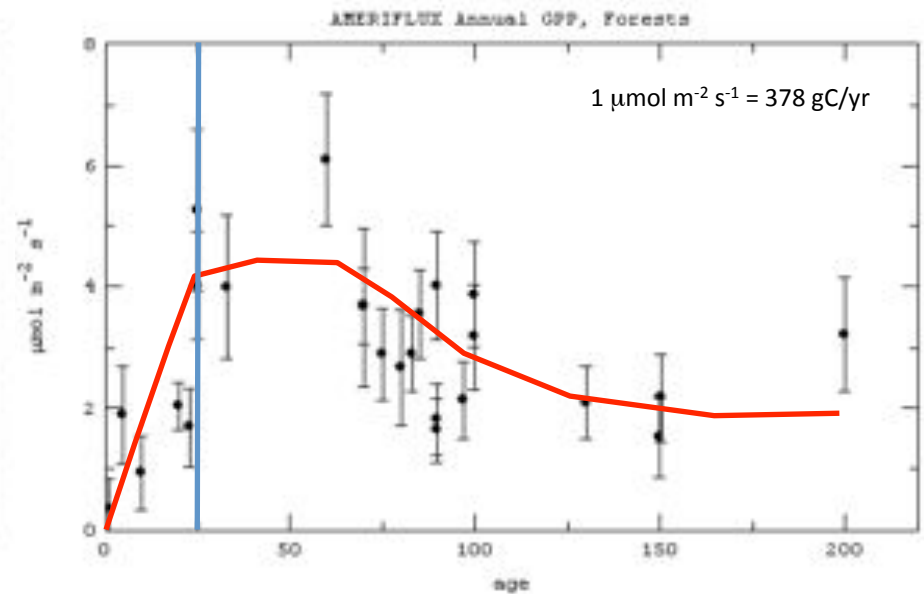
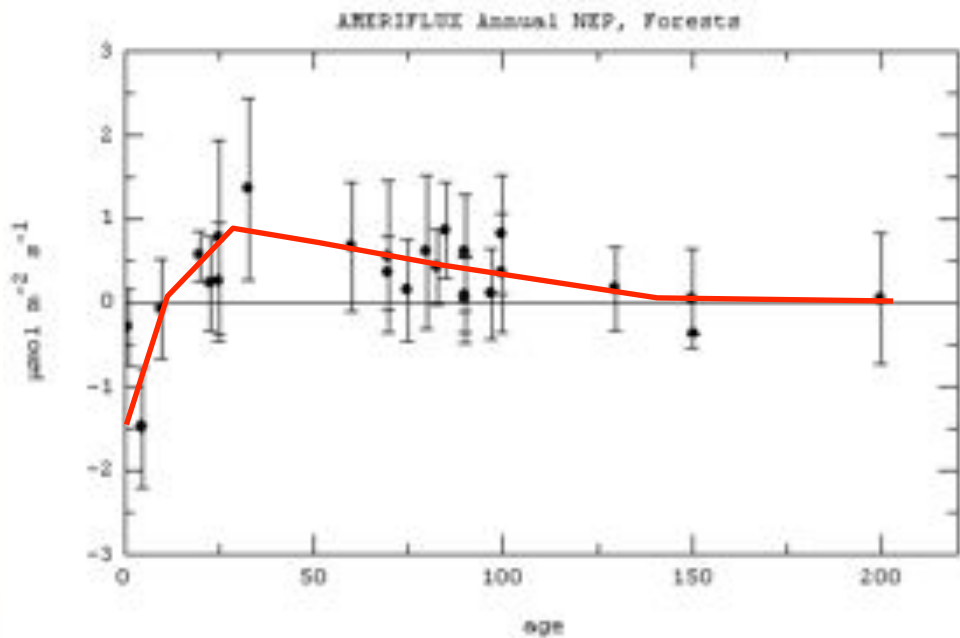
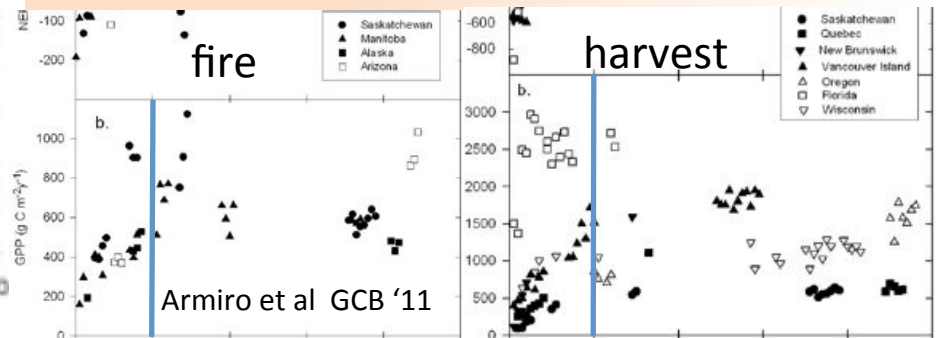
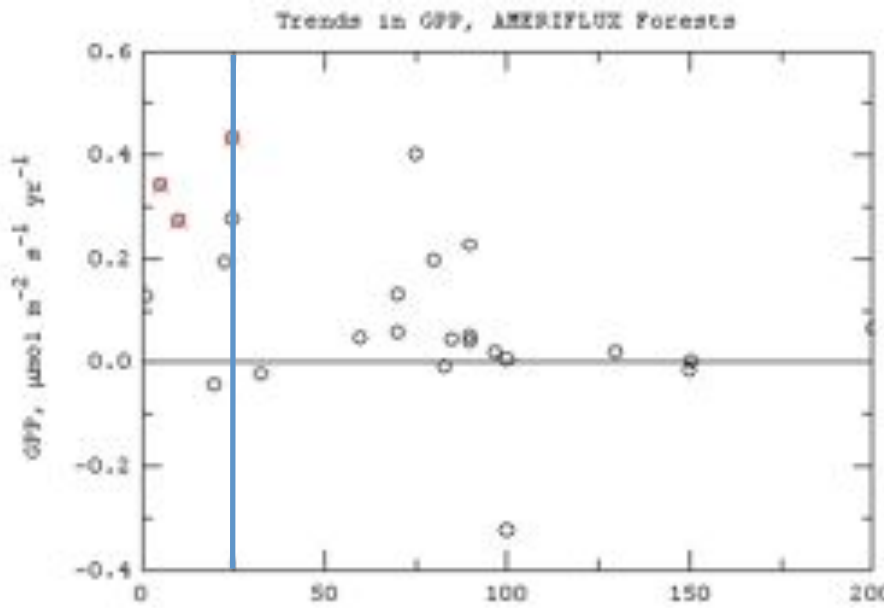
Age-weighted Growth Enhancement by FIA Type/Region



Evidence for Enhancement in Eddy Covariance Measurements

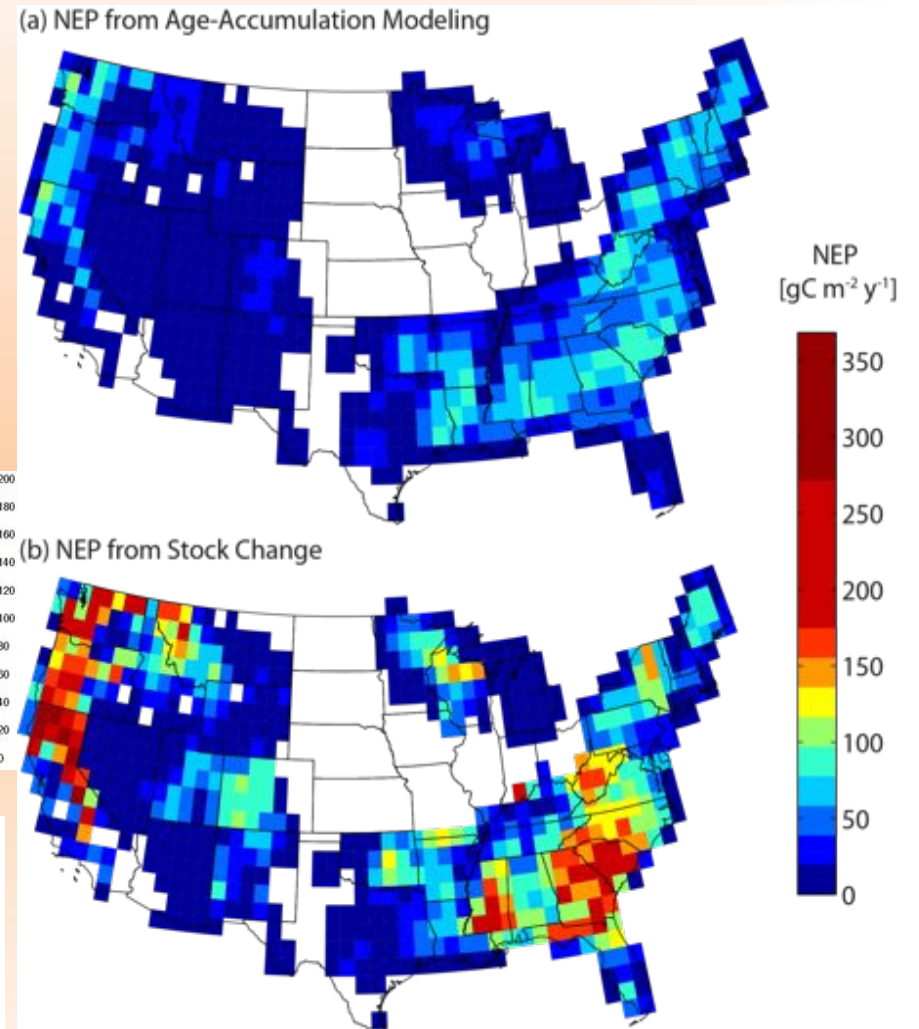
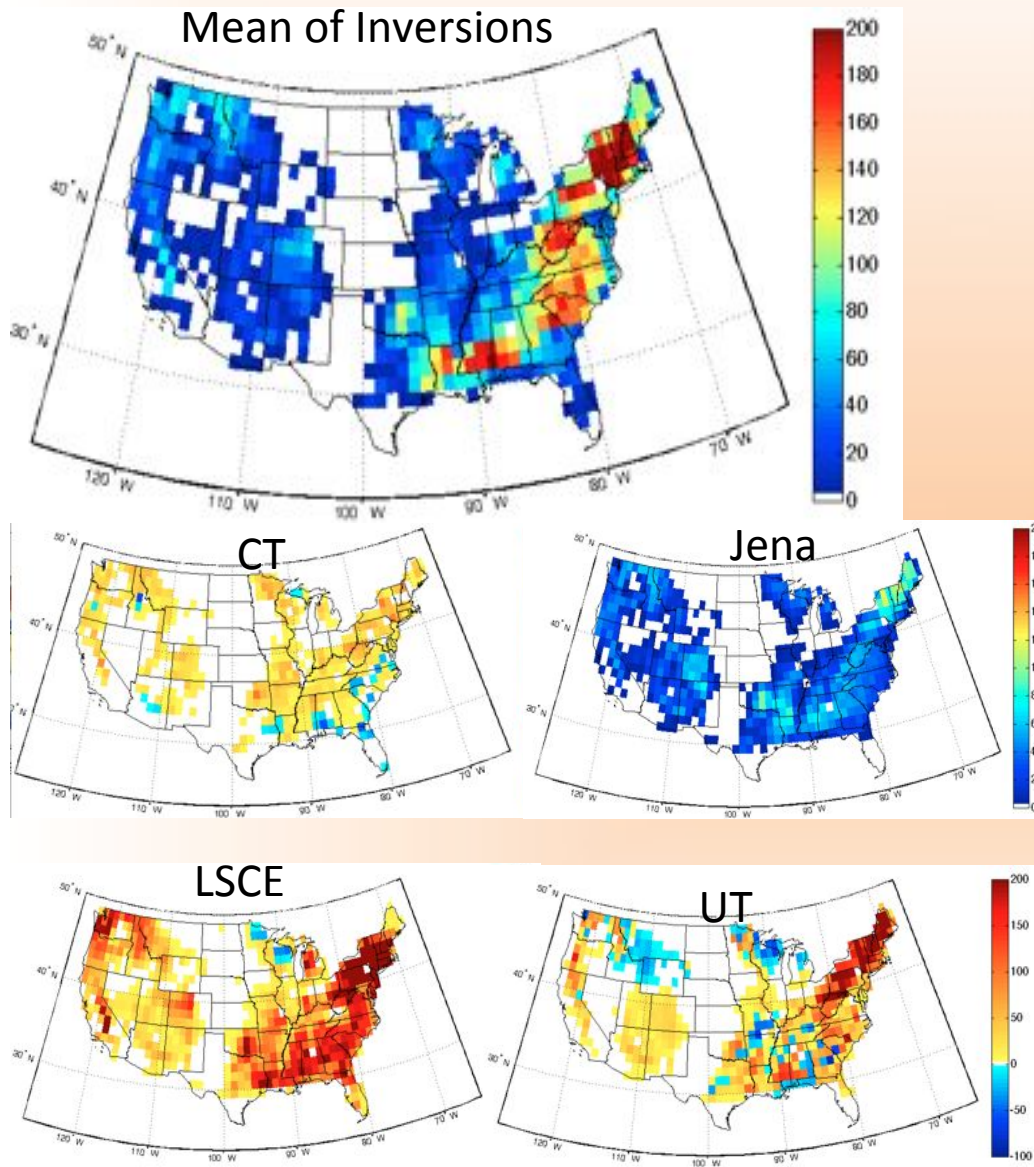
25 forest sites US and Southern Canada.

Most sites show positive trends in GPP
 Not expected based understanding of
 Regrowth dynamics



Data courtesy of K. Schaefer

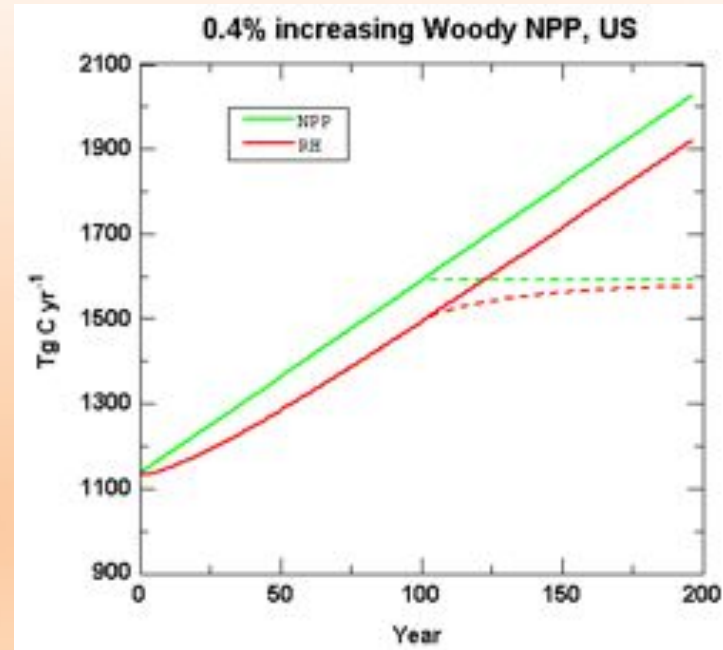
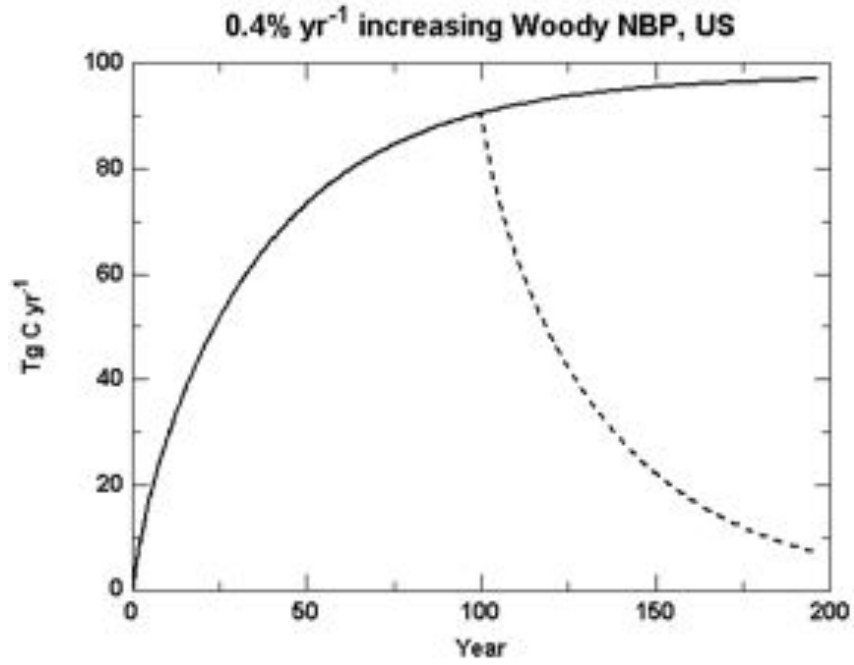
Inversions can't yet reconcile magnitude and distribution of Forest Sinks



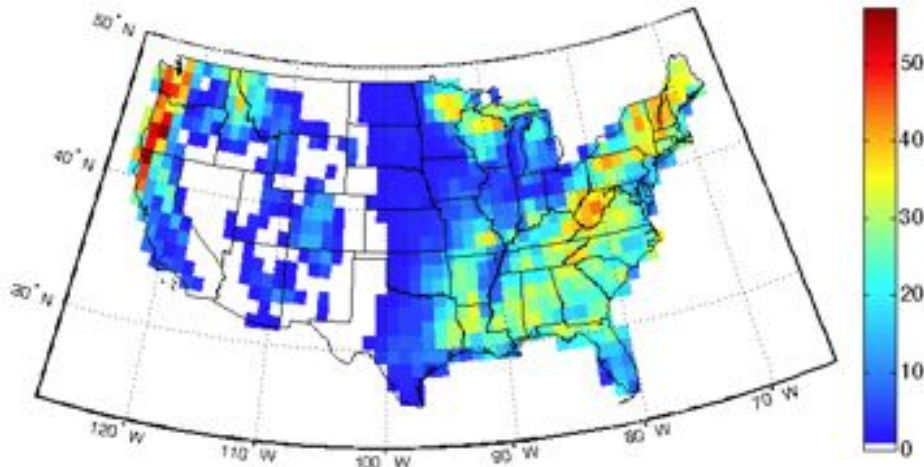
Growth Enhancement Scenario:

Increase Wood NPP at 0.4% / yr for 100 years

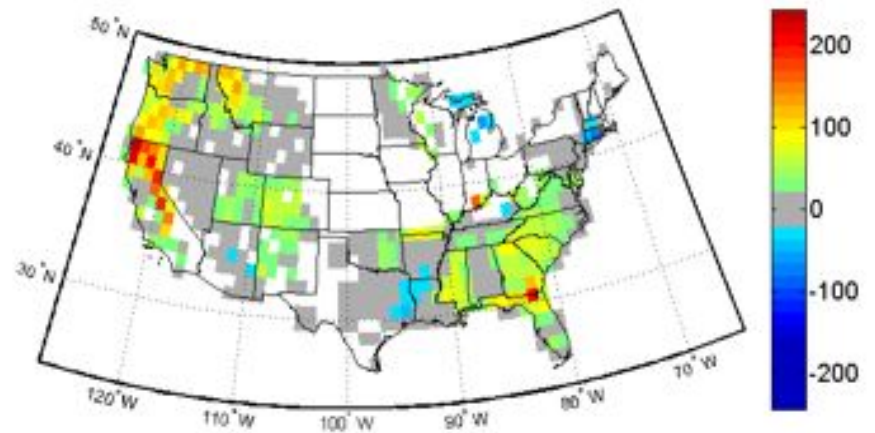
Produces a 90 Tg C / yr Sink



US NEPwood in 1850 with NPPwood increasing at 0.4% of initial NPPwood from 175



Mean Sink Enhancement [gC m⁻² y⁻¹]



Conclusions

Modeling disturbance and regrowth effects on forest NEP accounts for only half of the carbon sink seen in US stock changes

The additional sink is likely due to growth enhancements (climate trends, CO₂ fertilization, nitrogen fertilization, irrigation)

Enhancement is concentrated in regions with active management and younger and more productive forests (SE, SC, PNW, PSW)

Enhancement is supported by a number of lines of evidence.

The mechanisms driving the enhancement are unclear.

Note the Size of the enhancement exceeds expected CO₂ fertilization effects so positive feedbacks with other factors are required



Current and Future Work

- ◆ Wall-to-Wall CONUS VCT Products (PI: Goward)
- ◆ Expand spatial domain to Canada and Alaska
- ◆ Improved representation of disturbance type (fire, harvest, insect driven mortality)
- ◆ Derive finer spatial scale calibrations from FIA (state?) and account for thinning.
- ◆ Address the issue of what if anything is causing large scale growth enhancement
- ◆ Evaluate ability to detect/quantify forest source/sinks from observed atmospheric CO₂ variability (Kawa et al.)

Detecting and Quantifying Vegetation Responses to Climate Variability Using NDVI

Jim Collatz, Fanwei Zeng, Alvaro Ivanoff, Jorge Pinzon

In support of and supported by several projects (GFED, CMS, Kawa)

Rational: NDVI is used to drive the carbon cycle in diagnostic models like CASA. It is assumed that some part of NDVI variability represents real responses of vegetation to climate in these models. To do a better job at predicting interannual variability in the carbon cycle we need to understand the sources of variability in the models.

How much of the NDVI variability is caused by real climate response of the vegetation?

Data Sets:

NDVI: GIMMSg AVHRR, MODIS Terra, MODIS Aqua

Temperature: GISS and CRU

Precipitation: GPCP, TRMM

Other:

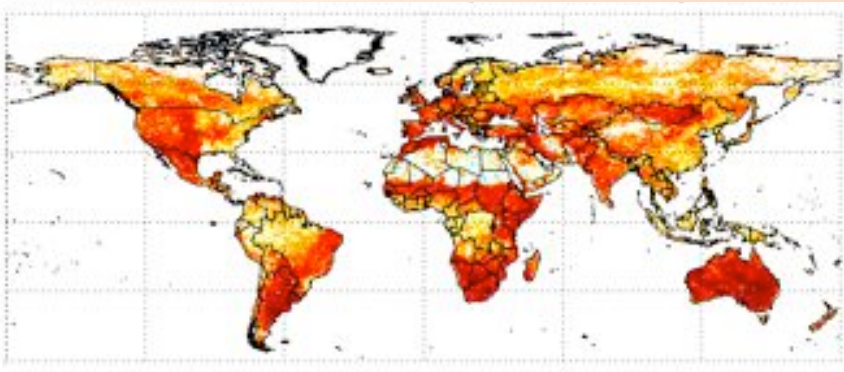
MODIS Snow Cover, MODIS Aerosol OD, MODIS Cloud Cover, GISS Solar Radiation

Weakness in AVHRR addressed by MODIS: degradation of calibration, drift, other BRDF, narrower bands (corrections for water vapor and aerosols), resolution.

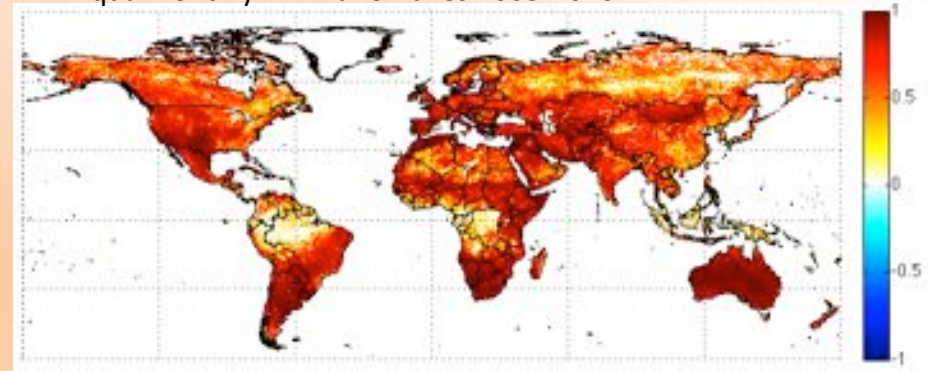
Advantages of AVHRR (esp GIMMSg): long timer period (more robust detection of climate signal), long experience with data (> 25 years)

GIMMSg NDVI captures same climate (and noise) driven variability as MODIS

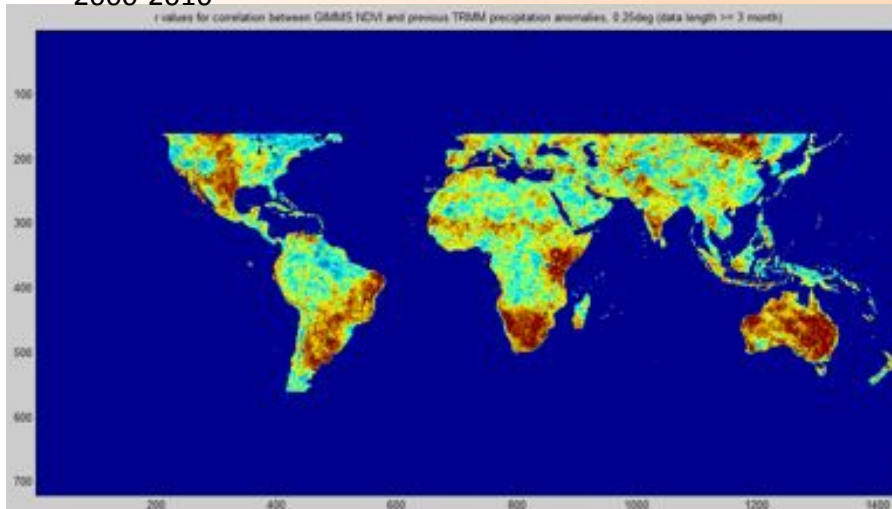
(a) Significant correlations ($p < 0.05$) between GIMMS and MODIS Aqua monthly NDVI anomalies, 2003-2010



(b) Significant correlations ($p < 0.05$) between MODIS Terra and Aqua monthly NDVI anomalies 2003-2010



Significant correlations ($p < 0.05$) between GIMMS monthly NDVI anomalies and antecedent TRMM precipitation, 2000-2010



Significant correlations ($p < 0.05$) between MODIS monthly NDVI anomalies and antecedent TRMM precipitation, 2000-2010

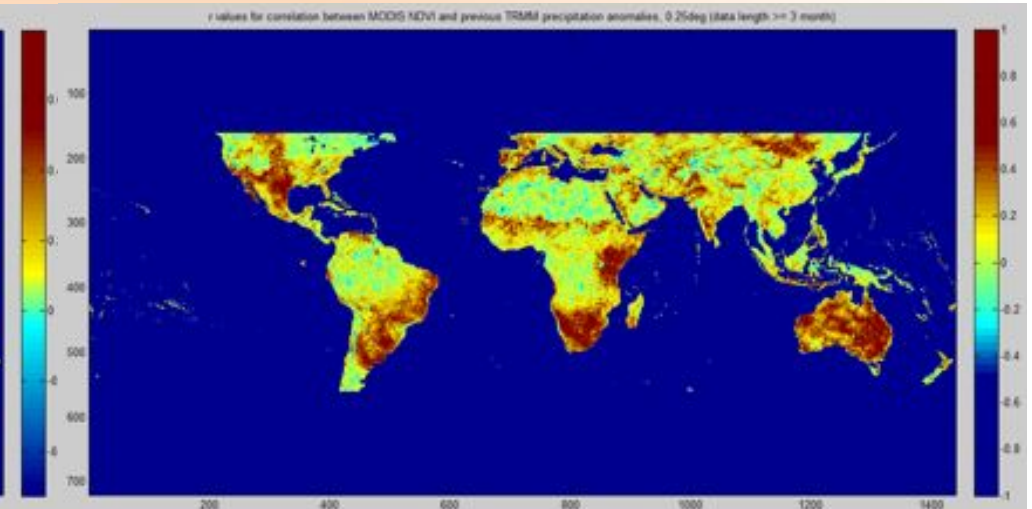


Figure 4. Global maps of month-specific correlation coefficients between GIMMS NDVI and cumulative GPCP precipitation (1-6 month lead) for 1982-2010 ($n = 29$). Only correlations significant at 95% confidence level are shown. (Spatial resolution: $1^\circ \times 1^\circ$. NH: Northern Hemisphere; SH: Southern Hemisphere)

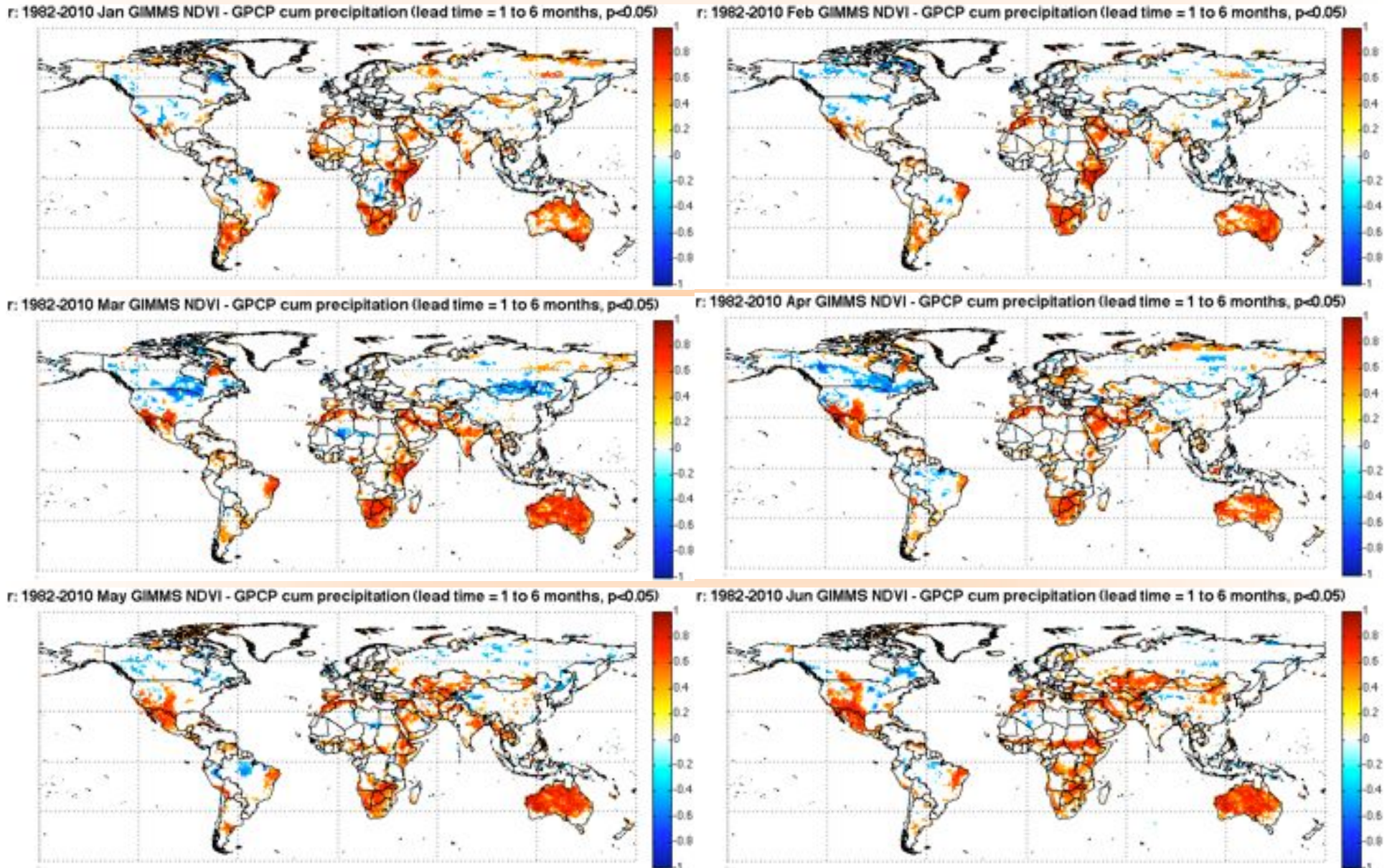
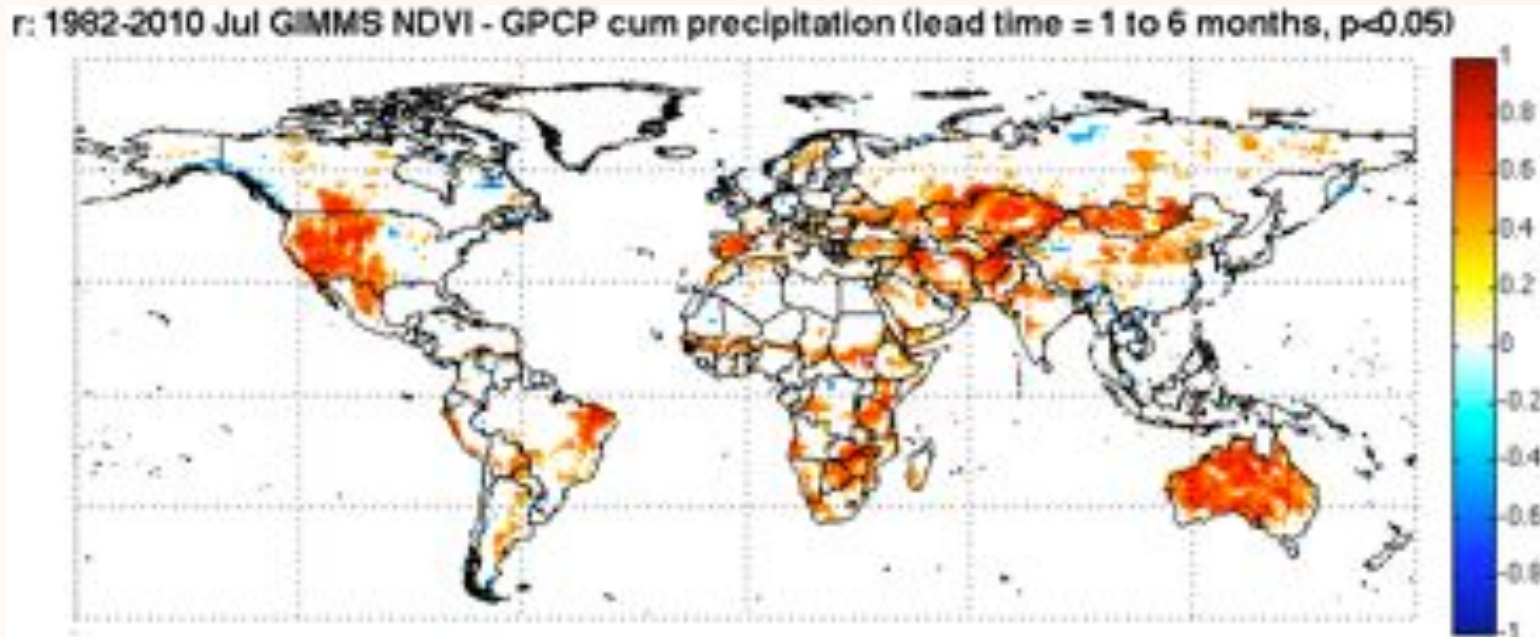
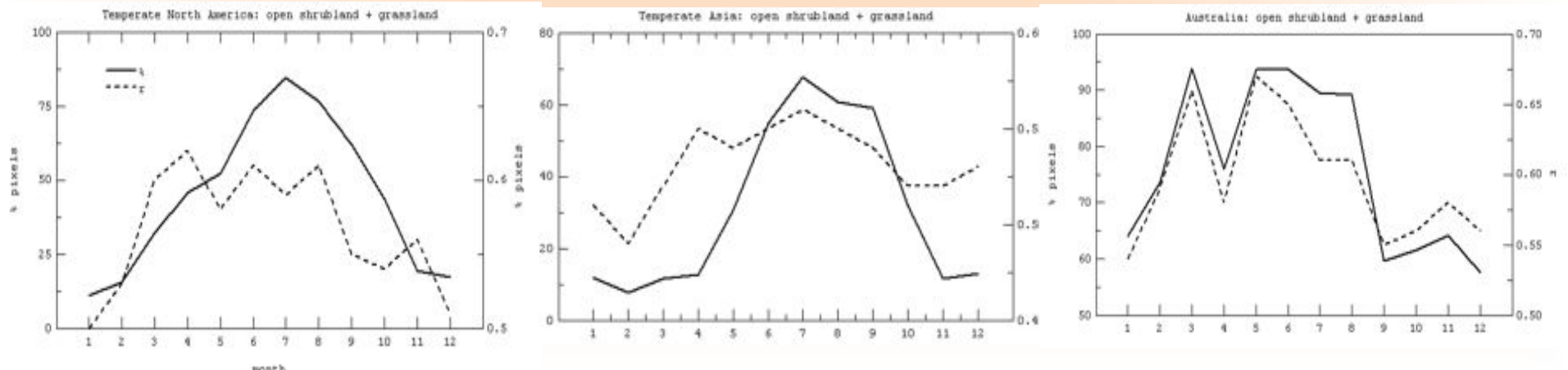


Figure 4. The correlation coefficients between GIMMS NDVI and cumulative GPCP precipitation (1-6 month lead) the month of July, 1982-2010 (n = 29). Only correlations significant at 95% confidence level are shown.



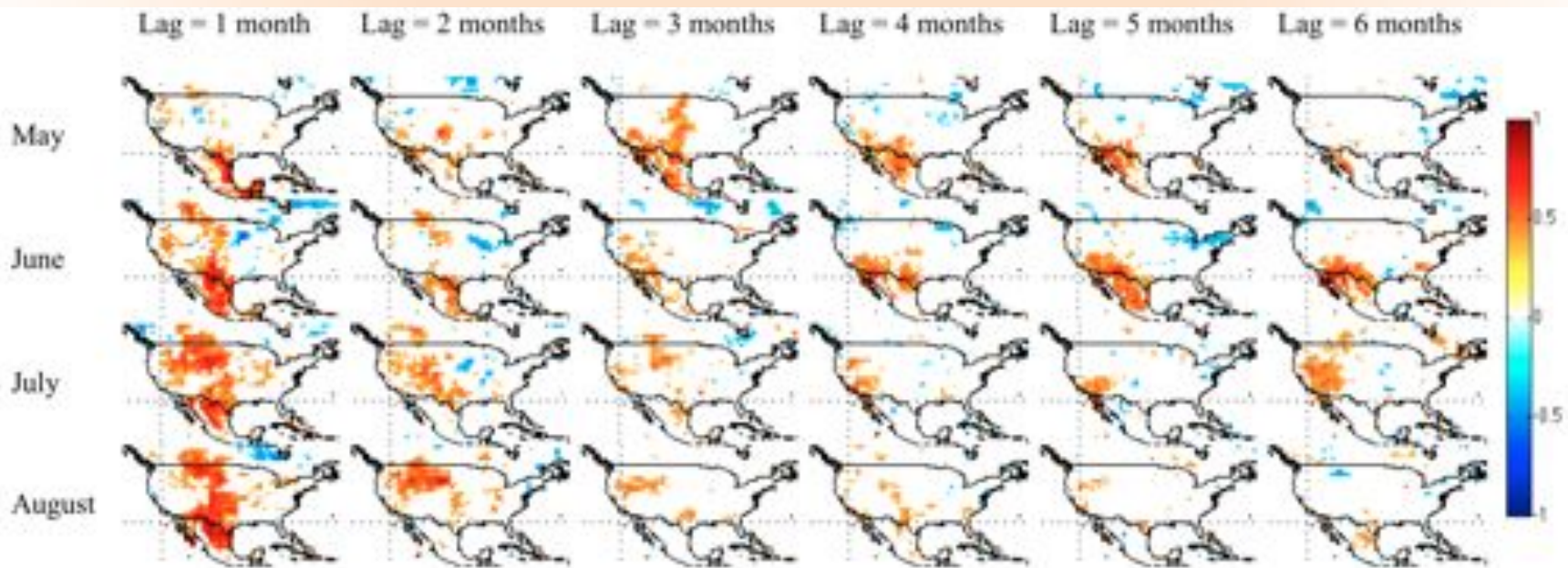
pixel % that show significant positive correlation (95% confidence level) and average correlation coefficient aggregated into certain vegetation classes and regions. Regions and classes are examples where high correlations occurred.



Correlations show that NDVI captures the seasonal dynamics of ecohydrology

Figure 5. Regional maps of month-specific GIMMS NDVI and GPCP precipitation correlations with varying lags (n = 29).

(a) North America:

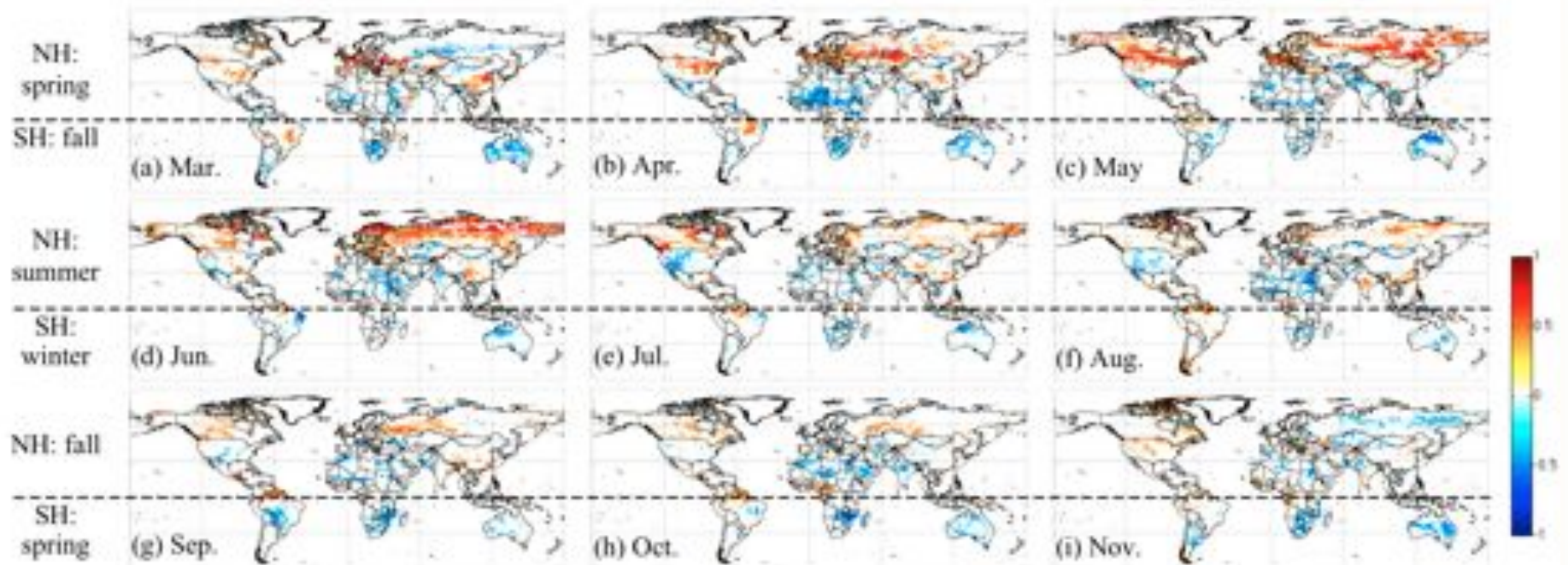


Early in the North American growing season vegetation growth is sensitive to cumulative antecedent precipitation from winter

Late in the growing season vegetation is more sensitive to recent precipitation, similar behavior in Africa and Australia.

Significant ($p < 0.05$) correlations between temperature and NDVI anomalies

Figure 7. Global maps of month-specific correlation coefficients between GIMMS NDVI and GISS temperature anomalies with lag = 0 month for 1982-2010 ($n = 29$), after removal of pixels with significant negative correlation between GIMMS NDVI and MODIS Terra snow cover. Only correlations significant at 95% confidence level are shown. (Spatial resolution: $0.5^\circ \times 0.5^\circ$, NH: Northern Hemisphere; SH: Southern Hemisphere)

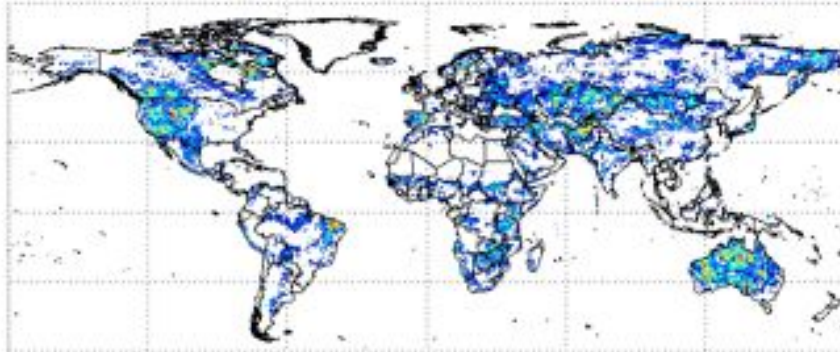


Note: negative correlations are associated with negative correlations between precipitation and temperature
-water limited conditions

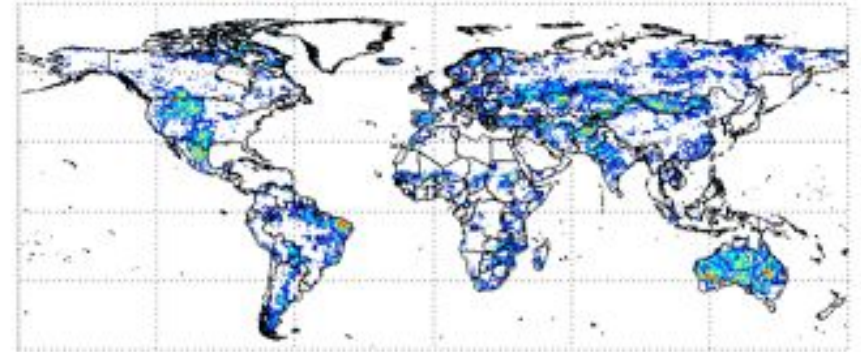
NDVI and temperature anomalies are correlated with the onset of spring in northern latitudes

The variance in NDVI explained by “real” vegetation responses to climate

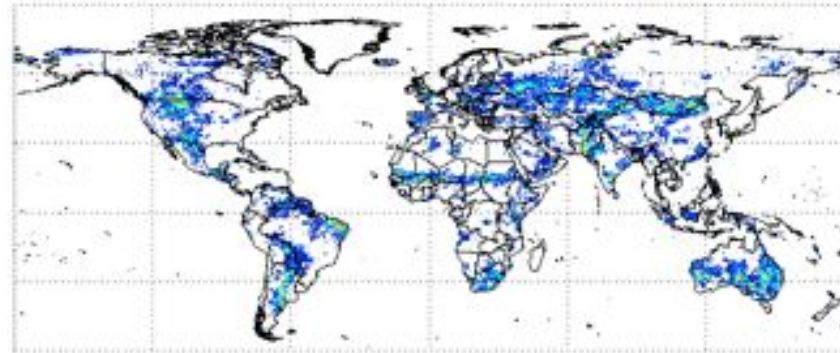
r^2 sum (82-10, Jul): positive GIMMS NDVI - cum GPCP and GISS ($p < 0.05$, no snow)



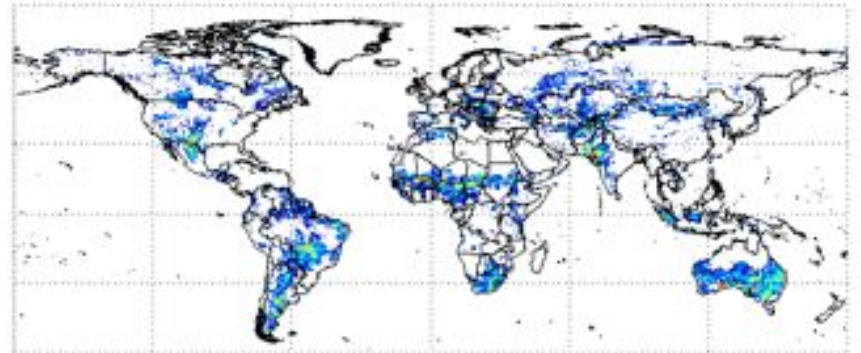
r^2 sum (82-10, Aug): positive GIMMS NDVI - cum GPCP and GISS ($p < 0.05$, no snow)



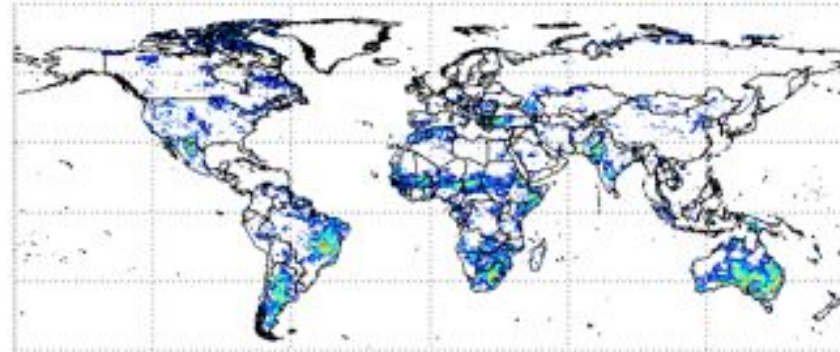
r^2 sum (82-10, Sep): positive GIMMS NDVI - cum GPCP and GISS ($p < 0.05$, no snow)



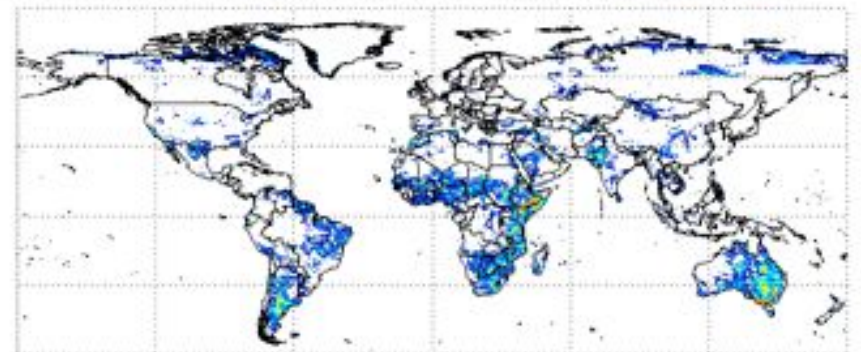
r^2 sum (82-10, Oct): positive GIMMS NDVI - cum GPCP and GISS ($p < 0.05$, no snow)



r^2 sum (82-10, Nov): positive GIMMS NDVI - cum GPCP and GISS ($p < 0.05$, no snow)



r^2 sum (82-10, Dec): positive GIMMS NDVI - cum GPCP and GISS ($p < 0.05$, no snow)

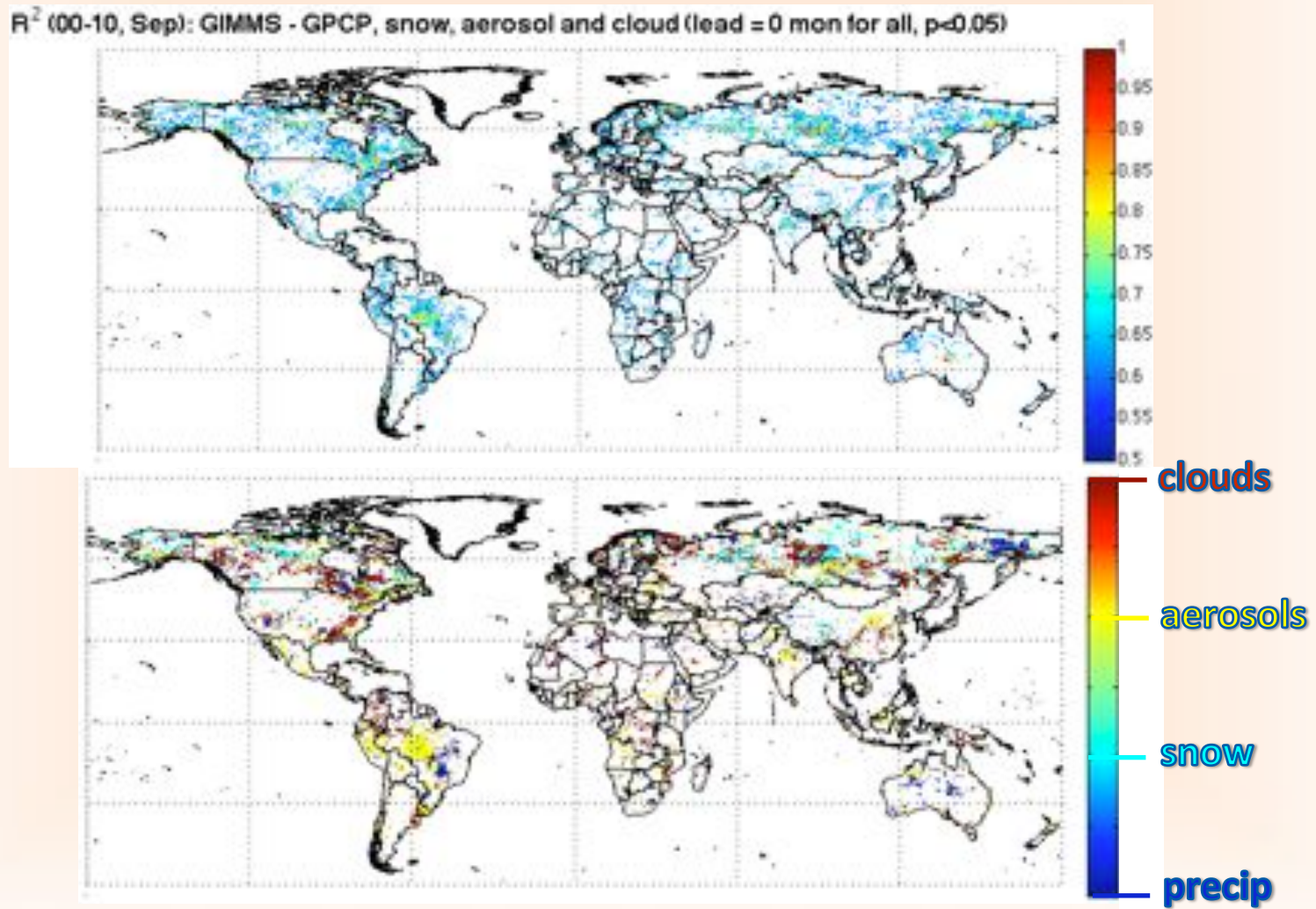


Variance in NDVI caused by noise

Variance in NDVI explained by current month precip, snow, aerosols, and clouds

Example: September

**Note all correlations are negative



NDVI interannual monthly variance explained by:

- “real” climate responses
- - - Interference from snow, precipitation, clouds and aerosols
- Remaining unexplained causes

