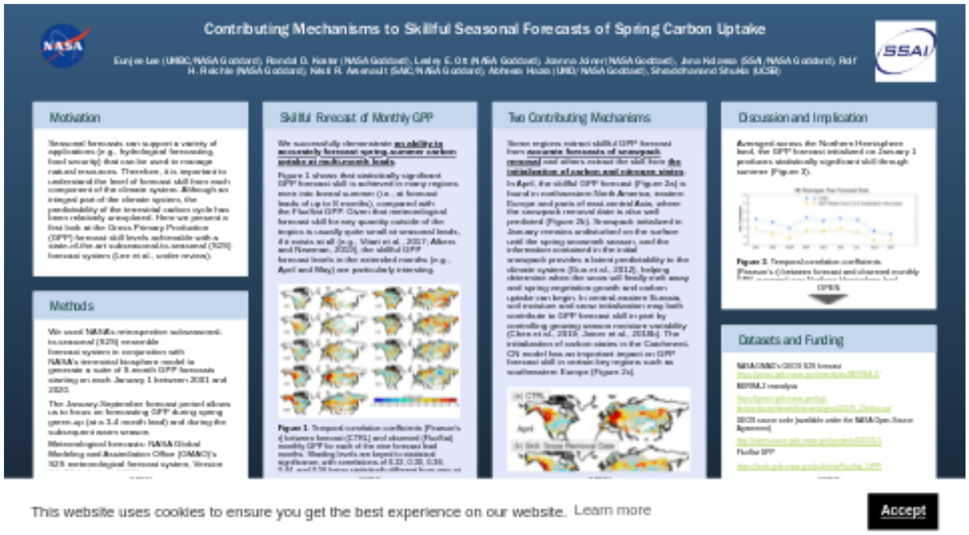
Contributing Mechanisms to Skillful Seasonal Forecasts of Spring Carbon Uptake



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PRESENTED AT:

MOTIVATION

Seasonal forecasts can support a variety of applications (e.g., hydrological forecasting, food security) that can be used to manage natural resources. Therefore, it is important to understand the level of forecast skill from each component of the climate system. Although an integral part of the climate system, the predictability of the terrestrial carbon cycle has been relatively unexplored. Here we present a first look at the Gross Primary Production (GPP) forecast skill levels achievable with a state-of-the-art subseasonal-to-seasonal (S2S) forecast system (Lee et al., under review).

METHODS

We generated a suite of 9-month (January-September) retrospective GPP forecasts. All forecasts were initialized on January 1 of each forecast year between 2001 and 2020.

For each of the nine forecast lead months, we evaluated the 20-year forecast skill of monthly GPP with an independent observational dataset (FluxSat GPP) derived from high-quality MODIS surface reflectance data (Joiner et al., 2018a; Joiner and Yoshida, 2020).

▸ Meteorological forecasts

NASA Global Modeling and Assimilation Office (GMAO)'s S2S meteorological forecast, Version 2.1 (Molod et al., 2020). Bias-corrected as in Arsenault et al. (2020) and Shukla et al. (2020).

▸ Terrestrial biosphere model

Catchment-CN (Koster et al., 2014) in a land-only configuration (offline mode) at a spatial resolution of 9 km.

▸ Initial state for January 1 of each forecast year

Prepared from the long-term simulation of Catchment-CN model, driven by Modern-Era Retrospective analysis for Research and Applications, Version 2 (MERRA-2) reanalysis data (Gelaro et al., 2017).

▸ Experimental design (CTRL and EXP)

[CTRL] 80 offline forecast simulations with Catchment-CN (four ensemble members per forecast year), starting on each January 1 between 2001 and 2020. The land-only simulations can be considered true forecasts, as they employed no observational information from within the forecast periods.

[EXP] Same as CTRL, but the only source of forecast skill in EXP was the initialization of multiple land surface carbon and nitrogen states. All information contained within the forecast meteorology and in the initialization of the land surface water and energy states (soil moisture, snow, temperature) was artificially removed from the forecasts, by using forecast meteorological forcing for 2013 and land surface water and energy initializations for 2013 during each forecast year.

SKILLFUL FORECAST OF MONTHLY GPP

We successfully demonstrate **an ability to accurately forecast spring-summer carbon uptake at multi-month leads**.

Figure 1 shows that statistically significant GPP forecast skill is achieved in many regions even into boreal summer (i.e., at forecast leads of up to 8 months), compared with the FluxSat GPP. Given that meteorological forecast skill for any quantity outside of the tropics is usually quite small at seasonal leads, if it exists at all (e.g., Vitart et al., 2017; Albers and Newman, 2019), the skillful GPP forecast levels in the extended months (e.g., April and May) are particularly intersting.

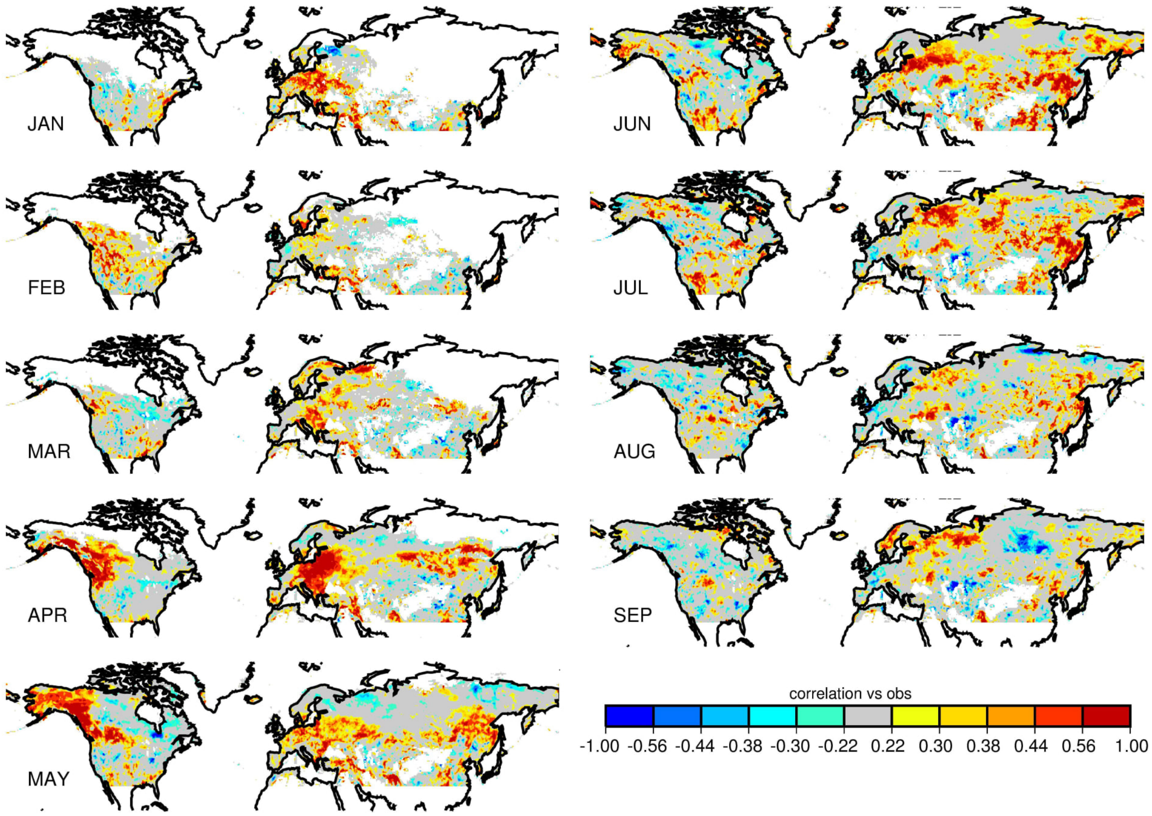

Figure 1. Temporal correlation coefficients (Pearson's r) between 20-year (2001-2020) forecast (CTRL) and observed (FluxSat) GPP for each of the nine forecast lead months. Note that all forecasts were intialized on January 1. Shading levels are keyed to statistical significance, with correlations of 0.22, 0.30, 0.38, 0.44, and 0.56 being statistically different from zero at the 66.7%, 80%, 90%, 95% and 99% confidence levels, respectively. Locations for which modeled GPP is undefined (e.g., due to desert conditions or snow cover) are masked out.

TWO CONTRIBUTING MECHANISMS

Some regions extract skillful GPP forecast from **accurate forecasts of snowpack removal** and others extract the skill from **the initialization of carbon and nitrogen states**.

In April, the skillful GPP forecast (Figure 2a) is found in northwestern North America, eastern Europe and parts of east-central Asia, where the snowpack removal date is also well predicted (Figure 2b). Snowpack initialized in January remains undisturbed on the surface until the spring snowmelt season, and the information contained in the initial snowpack provides a latent predictability to the climate system (Guo et al., 2012), helping determine when the snow will finally melt away and spring vegetation growth and carbon uptake can begin. In central-eastern Eurasia, soil moisture and snow initialization may both contribute to GPP forecast skill in part by controlling growing season moisture variability (Chen et al., 2019; Joiner et al., 2018b). The initialization of carbon states in the Catchment-CN model has an important impact on GPP forecast skill in certain key regions such as southeastern Europe (Figure 2c).

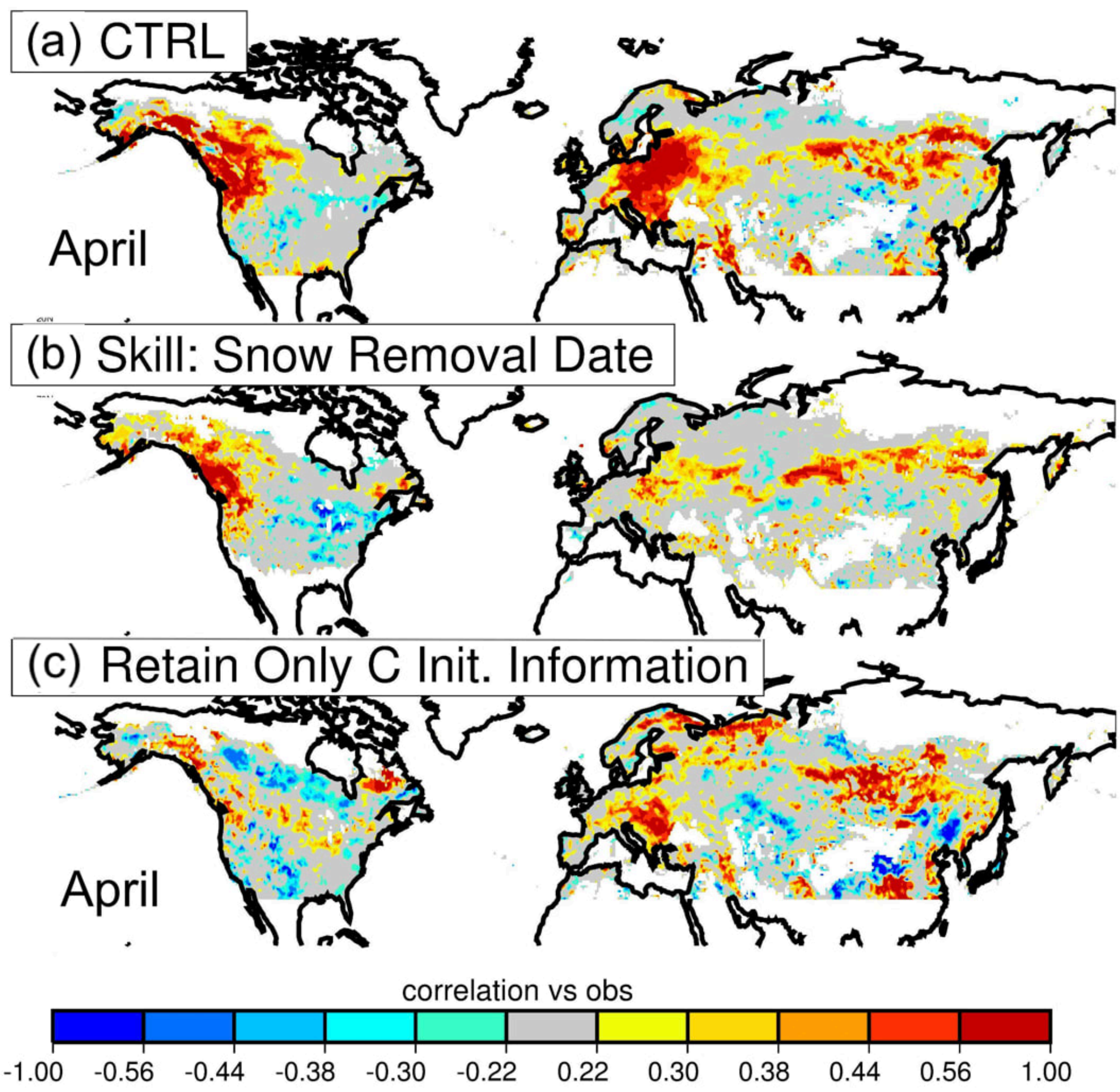

Figure 2. (a) Forecast skill for April: temporal correlation coefficients between forecast (CTRL) and observed (FluxSat) April GPP. (b) Temporal correlation between forecasted snow removal date and reanalysis-based (MERRA-2) snow removal date. (c) As in (a), but for the supplemental forecast suite (EXP) in which only the information contained within carbon reservoir initialization is utilized. In all plots, shading levels are keyed to

statistical significance, with correlations of 0.22, 0.30, 0.38, 0.44, and 0.56 being statistically different from zero at the 66.7%, 80%, 90%, 95% and 99% confidence levels, respectively. Locations for which modeled GPP is undefined (e.g., due to desert conditions or snow cover) are masked out.

DISCUSSION AND IMPLICATION

Averaged across the Northern Hemisphere land, the GPP forecast initialized on January 1 produces statistically significant skill through summer (Figure 3).

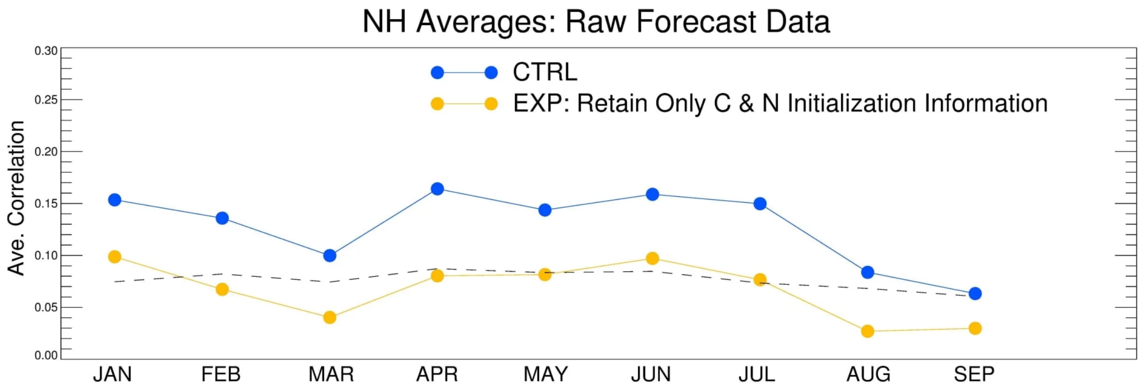

Figure 3. Temporal correlation coefficients (Pearson's r) between forecast and observed monthly GPP, averaged over Northern Hemisphere land points for the two sets of forecast simulations (CTRL, EXP) for each of the nine forecast lead months. Values above the dashed line are statistically different from zero at the 99% confidence level.

Overall, this study reveals some unexplored facets of climate predictability and **provides a look at what might be possible with future S2S forecast systems that are fully integrated with biogeochemical cycles**.

DATASETS AND FUNDING

NASA GMAO's GEOS S2S forecast https://gmao.gsfc.nasa.gov/reanalysis/MERRA-2/ (https://gmao.gsfc.nasa.gov/reanalysis/MERRA-2/)

MERRA-2 reanalysis

https://gmao.gsfc.nasa.gov/cgi-bin/products/climateforecasts/geos5/S2S_2/index.cgi (https://gmao.gsfc.nasa.gov/cgi-bin/products/climateforecasts/geos5/S2S_2/index.cgi)

GEOS source code (available under the NASA Open-Source Agreement)

http://opensource.gsfc.nasa.gov/projects/GEOS-5 (http://opensource.gsfc.nasa.gov/projects/GEOS-5)

FluxSat GPP

https://avdc.gsfc.nasa.gov/pub/tmp/FluxSat_GPP/ (https://avdc.gsfc.nasa.gov/pub/tmp/FluxSat_GPP/)

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ABSTRACT

Forecasting the uptake of carbon at seasonal lead times is challenging because of the uncertainties in seasonal meteorological forecasts and the complex feedbacks between the energy, water, and carbon cycles. Here, using a state-of-the-art seasonal forecast system, we demonstrate an ability to accurately forecast spring carbon uptake at multi-month lead times. Twenty 6-month forecasts of meteorology from NASA's subseasonal-to-seasonal (S2S) ensemble forecast system, each forecast beginning in a particular January during 2001-2020, are used to drive an offline terrestrial biosphere model. The resulting prediction of spring Gross Primary Production (GPP) is then evaluated against a fully independent, observational dataset derived from high quality MODerate-resolution Imaging Spectroradiometer (MODIS) reflectances. We find skillful forecasts of spring GPP in western North America, Europe, and parts of Asia. We can attribute the skill in western North America during boreal spring to meteorological variability, which is naturally tied to the amount of snow at the start of the forecast and its coupling to air temperature; the skill largely occurs where we have skillful forecasts of snow cover removal date and greening onset date. The forecast skill in Europe and central Asia is presumably attributable in part to a realistic forecast of soil moisture availability through a proper snow and soil moisture initialization. In late spring/early summer, the initialization in our offline forecasts of the carbon and vegetation variables appears to contribute to GPP prediction skill in Europe and parts of east Asia. Overall, this study highlights the significance of accurate land initialization (in particular, the initialization of the midwinter snow and the carbon and vegetation prognostic variables) for forecasts of GPP at seasonal lead times.

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