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PCIC SCIENCE BRIEF: HUMAN-INDUCED GREENING OF THE NORTHERN EXTRATROPICAL LAND SURFACE

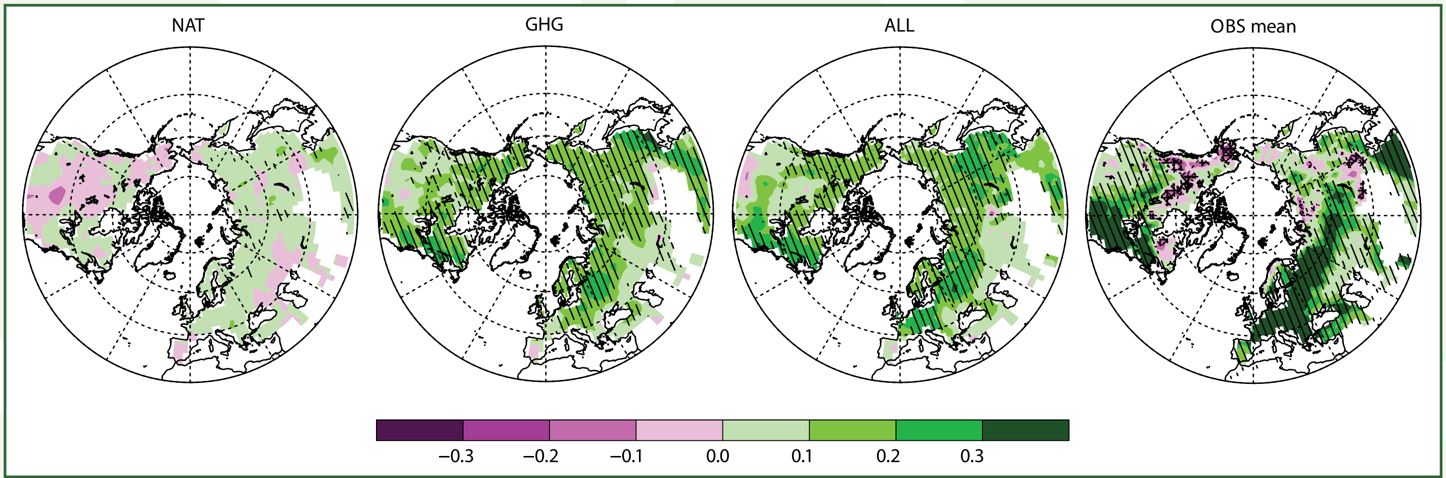

Figure 1: 1981-2011 Leaf Area Index trends, from Mao et al. (2016).
The panels show the spatial trends in Leaf Area Index in square metres of leaf area per square metre of land area over 30 years). The far-left panel, NAT, shows the change in leaf area index observed in the output of those climate models participating in the fifth phase of the Coupled Model Intercomparison Project[6] (CMIP5) and driven by natural forcings alone. The middle-left panel, GHG, shows the same thing for CMIP5 simulations driven by anthropogenic greenhouse gas forcings alone. The middle-right panel, ALL, shows the response from CMIP5 simulations driven by both natural forcings and anthropogenic greenhouse gas forcings. For these three panels, hatching indicates that at least 90% of the CMIP5 simulations agree on the direction (increasing or decreasing) of the trend. The far-right panel, OBS Mean, shows the average of two trend estimates from two sets of observational satellite data. Here, hatching indicates that both data sets agree on the direction (increasing or decreasing) of the trend.

Recent research by Mao et al. (2016) published in *Nature Climate Change* finds that the observed greening of the land surface between 30-75° north over the 1982-2011 period is largely due to anthropogenic greenhouse gas emissions.

Satellite records that extend back to the early 1980s show an overall, long-term greening trend[1] over the Earth's surface[2]. This global trend in increased leaf coverage has been attributed to a number of factors. The most important of these is the increasing concentration of carbon dioxide in the atmosphere, which plants use for photosynthesis and growth. Another is changes in the rate at which nitrogen, a nutrient required for growth, is deposited into ecosystems. Still others include the direct effects of climate change and changes in how land is used and managed, such as for forestry and agriculture. The greening is apparent on a global average, but is not uniform, with some areas, such as parts of northwestern North America and South America showing the opposite trend. Changes in forest vegetation due to climate change may result in impacts to ecosystems[3] and resulting changes to ecosystem services. They can also affect climate[4] through changes in the amount of evaporation and transpiration, reflected sunlight or ecosystem carbon dioxide uptake or release. Changes to forest cover may also be related to climate change elsewhere through long-distance "teleconnection" patterns[5].

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1. That is, there has been an increase in the Leaf Area Index (LAI), a scale that describes the amount of an area that is covered by leaves, with leaves that have a surface area ten times greater than the land area occupied by the forest. It runs from zero to ten, with zero being ground that is devoid of plant cover and ten being a very dense forest.
2. For more on the global trend including attribution work, see Zhu et al., 2016.
3. For possible impacts to forests in British Columbia and Canada, see Metsaranta et al., 2011 and Price et al., 2013.
4. For a discussion of the effects of forest on climate, see Bonan, 2016.
5. For more on possible teleconnection links between changes in forest cover and changes in climate, see Garcia et al., 2016.

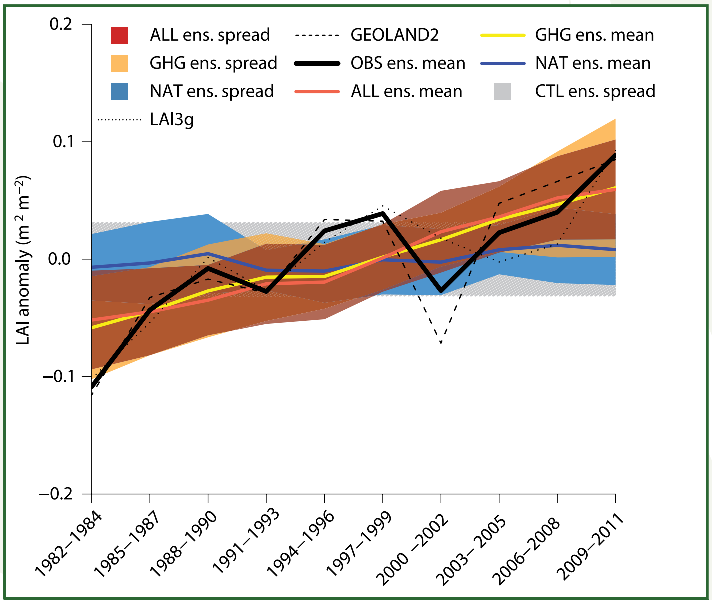

Figure 2: Leaf area index anomalies from Mao et al. (2016).

This figure shows LAI anomalies, both observed and simulated, over the growing season (April to October) in the northern extratropical land surface over the 1982-2011 period. Three-year-means are used. CMIP5 model output is used for GHG, NAT and ALL, which correspond to models driven by anthropogenic greenhouse forcings only, natural forcings only or both anthropogenic and natural forcings, respectively. LAI3g[7] and GEOLAND2[8] correspond to satellite data sets, with OBS being their mean. Colors correspond to datasets as indicated in the legend above. Ensemble spreads indicate the 5% to 95% uncertainty bands for the ensembles.

Publishing in *Nature Climate Change*, Mao and colleagues (2016) examine the role of anthropogenic greenhouse gas emissions in the portion of this greening that is occurring in the northern extratropical land surface. For their work, the authors define the northern extratropics as 30-75° north. This region extends as far south as the US-Mexican border and north into the Arctic Circle, including essentially all of Europe, most of Asia and some of northern Africa. The authors use two sets of satellite leaf area index observations[7] that derive leaf area from the amount of reflected light from land surfaces. They compare these with global climate model output from models participating in the fifth phase of the Coupled Model Intercomparison Project (CMIP5[6]). We can see the overall greening of the northern extratropical land surface in the observational data, in the far right panel of Figure 1. Comparing this panel with the three on its left, which show the output from climate models driven with only natural forcings, only anthropogenic greenhouse gas forcings (GHG) and all forcings, it is apparent that the simulations driven with all forcings and the GHG forcing more closely match the observations than those driven with natural forcings alone. The GHG and all forcing simulations better capture the greening over most of North America and the stronger positive trends (darker green) over North America and Eurasia. The 30-year trends in the observations show an average increase in leaf area index of 0.153 square metres of leaf cover per square metre of ground over the northern extratropical land surface. The simulations show increasing trends of 0.017, 0.129 and 0.133 for those runs driven by natural, GHG and all forcings, respectively. Even when uncertainties are taken into account, Mao et al. note that the simulations driven with only natural forcings are inconsistent with observations. This can be seen in the growing season anomalies in Figure 2, in which the observations (black lines) fall outside of the blue shading that indicates the spread of the simulations from driven by natural forcings only, but falls mostly inside the orange and brown shading that indicates the spread of the output from simulations with GHG and all forcings, respectively.

The authors then use statistical tests[8] on the trends from the observational data that compare these trends with-those from the simulations mentioned above, as well as other simulations in which the models driven by only internal variability (i.e. no changes in atmospheric aerosols or the sun's output), only physiological effects and only GHG radiative feedbacks. Mao et al. find that the observed change in leaf area index during the growing season over the 1982-2011 period in the northern extratropics is consistent with simulations driven by GHGs and all forcings, but not consistent with simulations driven by natural forcings alone. This suggests that anthropogenic GHG emissions have played a role in the greening of this area. However, the authors also find that the errors in their statistical fit are larger than the internal variability[9] in the simulations, which may suggest that the models are underestimating some aspects of internal variability.

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[6] More information on the Coupled Model Intercomparison Project is available at: http://cmip-pcmdi.llnl.gov/.

[7] The authors use two different leaf area index data sets derived from satellite observations, LAI3g and GEOLAND2. Both LAI3g and GEOLAND2 use neural networks to infer leaf area indices from observations of reflectance from instruments on board satellites. More information on the development of LAI3g can be found in Zhu et al., 2013. For more on GEOLAND2, see Baret et al., 2013.

[8] The authors use a chi-squared test and an optimal fingerprinting technique (this can be interpreted as a regression technique or likelihood ratio test). For more on the chi-squared test, see the supplementary materials. For more on optimal fingerprinting, see Allen and Stott, 2003, and Ribes, Planton and Terray, 2013.

In determining what this means for British Columbia, we may be tempted to read the observational trends straight from Figure 1. However, we should note that the observed leaf areas are derived from light that is reflected from the landscape and then measured by satellites. As Mao and colleagues note, errors can be introduced by the presence of clouds, snow cover and other factors that affect the amount of reflected light that is measured by the satellite. These can include land use changes, such as forest management and forest disturbances, including the effects of the recent mountain pine beetle outbreak. In addition, the data set is comprised of observations from a variety of different satellites over decades. In that time, satellite sensor technology has changed. This can introduce deviations in the data that arise due to changing sensors, as opposed to changing conditions on the land's surface. The authors also did not test or analyze the data on scales as small as a province. So, caution would be advised in trying to infer trends for BC from the results of this paper.

However, some evidence for the effect of carbon dioxide fertilization on some locations in BC does exist. Direct measurements of trees in the field suggest that some of the province's temperate-maritime forests show an increasing trend in tree growth, partially due to carbon dioxide fertilization[10]. The Forest Carbon Management Project, an initiative of PCIC's sister organization, the Pacific Institute for Climate Solutions, has conducted simulations[11] of vegetation growth in BC over the 1900-2050 period. The results of this work suggest that vegetation biomass has been increasing since the 1950s and that this may continue until at least 2050, potentially offsetting losses from the mountain pine beetle outbreak. However, this research does not account for future insect outbreaks, the frequency of which may be affected by warming winters as the climate continues to change. So, we cannot yet say whether carbon dioxide fertilization will outweigh other factors affecting BC's forests.

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Price, D.T. et al., 2013: Anticipating the consequences of climate change for Canada's boreal forest ecosystems. *Environmental Reviews*, **21**, 4, 322–365, doi: 10.1139/er-2013-0042.

Ribes, A. S. Planton, and L. Terray, 2013: Application of regularised optimal fingerprinting to attribution. part I: method, properties and idealised analysis. *Climate Dynamics*, **41**, 2817–206 2836, doi:10.1007/s00382-013-1735-7.

Zhu, Z. et al., 2013: Global Data Sets of Vegetation Leaf Area Index (LAI)3g and Fraction of Photosynthetically Active Radiation (FPAR)3g Derived from Global Inventory Modeling and Mapping Studies (GIMMS) Normalized Difference Vegetation Index (NDVI3g) for the Period 1981 to 2011. *Remote Sensing*, **5**, 2, 927–948; doi:10.3390/rs5020927.

Zhu, Z., et. al., 2016: Greening of the Earth and its drivers. *Nature Climate Change*, **6**, 791–795, doi:10.1038/nclimate3004.

9. Owing to its complex and vastly coupled nature, the state of the climate system is affected not only by external forcings, such as changes in solar output and atmospheric greenhouse gas concentrations, but also patterns that can develop due to internal interactions between its various components. These include things such as shifts in patterns of atmospheric and ocean circulations, volcanic activity and fluctuations in the amount of the surface covered in ice and different types of vegetation.

10. For more see Hember et al., 2012.

11. For more on projected changes to BC's forests, see Arora et al. (2016).