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Working Paper

14-23

Earth's CO_2 Battle: A View from Space

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Earth's CO_2 battle: a view from space

Earth's environment is undergoing rapid change as greenhouse gases warm the planet. **Noel Cressie, Andrew Zammit-Mangion, Josh Jacobson, and Michael Bertolacci** use WOMBAT, a Bayesian hierarchical statistical framework, to infer the spatio-temporal distribution of CO_2 surface fluxes.

Greenhouses trap heat and, with ample water and fertile soil, they allow us to eat our favourite fruits and vegetables all year round. But could we live in one? We are about to find out, with our planet's atmosphere accumulating more and more of the gases that trap energy in the lower atmosphere after being reflected from Earth's surface. The main human-induced greenhouse gases are **carbon dioxide (CO_2)**, methane, nitrous oxide, and fluorinated gases in order of their effect on global warming. Scientists have known about the greenhouse effect for a long time (Foote, 1856; Aarhenius, 1896) but, in the last 60 years, atmospheric measurements of both meteorology and greenhouse gases have revealed its extent.

About three quarters of the global warming potential of all emitted greenhouse gases comes from CO_2. Emissions of CO_2 are dominated by the burning of fossil fuels (80%), but land use (in the form of clearing/burning of forests, grasslands, and savannas, and poorly practiced agriculture) represents a significant contribution as well (15%). A lot is known about these human-induced emissions, including that they result in an increase of about a 0.5% per year of atmospheric CO_2. In a geological blink of an eye (250 years, since the beginning of the industrial era), the atmospheric concentration of CO_2 has increased by about 50% and, in the last 60 years alone, emissions have risen from almost 10 billion tonnes/year of CO_2 to 40 billion tonnes/year of CO_2. Since 1 tonne of CO_2 contains 3/11 tonnes of carbon, every year our atmosphere is now receiving about 11 billion tonnes of carbon from human-induced CO_2 emissions! About half of it stays in the atmosphere, but where does the rest go?

Beginning in 1988, there ha been a series of United Nations (UN) assessment reports from the Intergovernmental Panel on Climate Change (IPCC) that have offered warnings about global warming due to greenhouse-gas emissions, the starkest coming from the latest report in 2021-2022. According to this Sixth Assessment Report (*Working Group I – The Physical Science Basis*; IPCC, 2021), "…limiting human-induced global warming to a specific level requires limiting cumulative CO_2 emissions, reaching at least net zero CO_2 emissions"; and following on (*Working Group II – Impacts, Adaptation and Vulnerability*; IPCC, 2022), "Widespread, pervasive impacts to ecosystems, people, settlements, and infrastructure have resulted from observed increases in the frequency and intensity of climate and weather extremes, including hot extremes on land and in the ocean, heavy precipitation events, drought and fire weather… Impacts in natural and human systems from slow-onset processes such as ocean acidification, sea level rise or regional decreases in precipitation have also been attributed to human induced climate change"

In December 2015, 196 countries and territories around the world participated in the UN's 21st Conference of the Parties (in Paris, France) and signed an agreement (COP21, 2015) to limit global warming to below 2-degrees and preferably 1.5-degrees Celsius, compared to pre-industrial global temperatures. Achieving this target requires a worldwide reduction in greenhouse-gas emissions, especially those of CO_2. It was agreed that a global stocktake of carbon stocks and emissions would happen every five years and would take two years to complete; the first stocktake began in 2021 at COP26 in Glasgow, Scotland, and it will conclude in 2023 at COP28 in the United Arab Emirates.

While fossil-fuel usage leads to emissions of CO_2, there are natural processes that both absorb and emit the gas. This is fortunate: As the human-induced sources have increased from 10 to 40 billion tonnes/year of CO_2, our planet's carbon cycle has adapted by increasing its natural land and ocean sinks and has managed to absorb about half of the CO_2 that humans emit (Crisp et al., 2022), but for how long? Quantifying the locations and times of natural sources and sinks (collectively, **natural fluxes**) of CO_2 at Earth's surface is therefore important, and even more so because human activities such as land usage are modifying the natural fluxes. However, while efforts to quantify fossil-fuel emissions can rely on well measured quantities such as power-plant emissions and ship/aircraft activity, such "bottom-up" approaches are more difficult and less accurate for estimating natural fluxes. An alternative is to use observations of atmospheric CO_2 concentrations, an approach known as **flux inversion**, which works backwards from the observed concentrations to estimate the temporal and geographical distribution of Earth's CO_2 sources and sinks.

The atmosphere is a connected system, and CO_2 molecules are constantly moving with the wind. This means that when CO_2 is emitted or absorbed in one region, it later affects CO_2 concentrations at other locations and altitudes around the globe. At the same time, natural fluxes are spatially and temporally heterogeneous: temperate forests occupy large parts of the terrestrial biosphere and transition from sinks to sources during the year, while volcanoes are local sources with sporadic and unpredictable emissions of CO_2. Although we have measurements of the atmospheric concentrations with global coverage, there are almost none on the fluxes themselves. Together, these features make CO_2 flux inversion (that will tell us how much, where, and when CO_2 is exchanged at Earth's surface) an ill-posed problem with inherent uncertainties in its solution. In this article we look at this problem through the eyes of **WOMBAT**, a Bayesian statistical flux-inversion framework that produces flux estimates as well as their uncertainties (Zammit-Mangion et al., 2022). WOMBAT uses statistical methods to identify and account for different sources of variability and uncertainty in the fluxes and the atmospheric concentrations, and it is designed to help scientists and policymakers make decisions about CO_2 mitigation in the presence of uncertainty.

WOMBAT: A fully Bayesian global flux-inversion framework

WOMBAT stands for **WO**llongong **M**ethodology for **B**ayesian **A**ssimilation of **T**race-gases, named for the Australian marsupial, shown in Image 1.

Image 1: A wombat pictured near Cradle Mountain in Tasmania, Australia. [Photo by Meg Jerrard]

We start by simulating the processes and measurements using an Observing System Simulation Experiment (OSSE). In an OSSE the true latent processes (here, the fluxes and the atmospheric CO_2 concentrations) are assumed known, and measurement error and missingness are also known. Then we are able to simulate synthetic observations from the latent processes at the same locations and times as the real observations. For example, to obtain Figure 1 we simulated the effect of additional CO_2 emissions (i.e., sources) over parts of North America using what is known as a **chemical transport model**. The left panel shows these emissions, and the right panel is a snapshot of how the extra CO_2 spreads around the globe. By adding together hundreds of such simulated changes in different parts of the globe, we can build a picture of how atmospheric transport works. In fact, CO_2 moves around the globe quite quickly and becomes part of the background concentration in the hemisphere where it is emitted within several months, compounding the difficulty of carrying out CO_2 flux inversions.

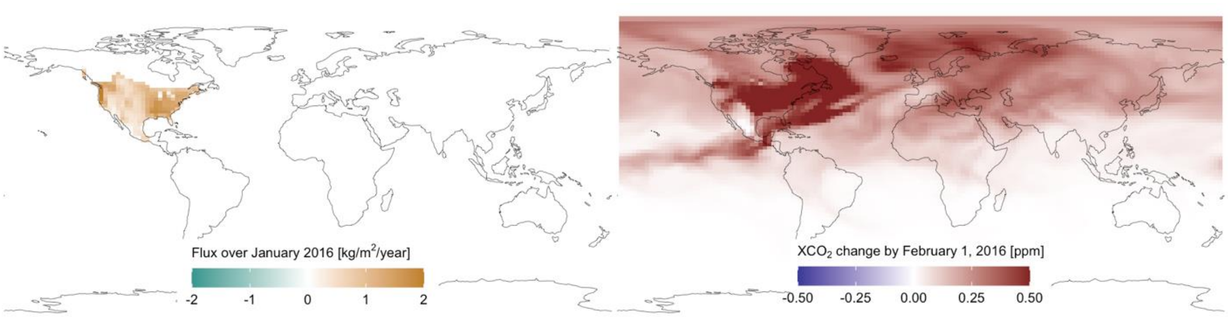

Figure 1: Estimated changes in atmospheric-column CO_2 concentrations (XCO_2) on 1 February 2016, in response to CO_2 emissions (fluxes) over January 2016 in North America. Left panel: Fluxes. Right panel: CO_2 concentrations.

Recall that while CO_2 flux is the key quantity, it is the downstream effect of fluxes, namely **atmospheric CO_2 concentrations**, that can be measured. Figure 2 shows an OSSE simulation of CO_2 concentrations (in parts per million) on the right, simulated from the corresponding fluxes (in kilograms per square metre per year) on the left. Our OSSE then samples from the global map on the right to obtain satellite-like observations of CO_2 concentrations. Thus, our Observing System produces realistic simulations of CO_2 satellite data from which flux-inversion experiments can be carried out.

With an understanding of atmospheric transport, WOMBAT takes observations of CO_2 concentrations and works backwards in a computationally efficient manner to estimate the CO_2 fluxes along with their uncertainties. The chemical transport model used by WOMBAT is called GEOS-Chem (e.g., Yantosca, 2019). Although geophysicists would like to get a perfect estimate of the CO_2 fluxes, the complexities of the atmosphere make this impossible. The WOMBAT framework quantifies uncertainties in the data and the geophysical processes in terms of conditional probabilities. This statistical framework is called a **Bayesian hierarchical model (BHM)**, and the statistical model in WOMBAT is a geophysical example of a BHM. In what is to follow, we give an intuitive explanation of the BHM for flux inversion, followed by a more technical one that makes use of **Bayes' Rule**. The bottom line is that WOMBAT produces a full posterior distribution of all unknown quantities but particularly the unknown fluxes.

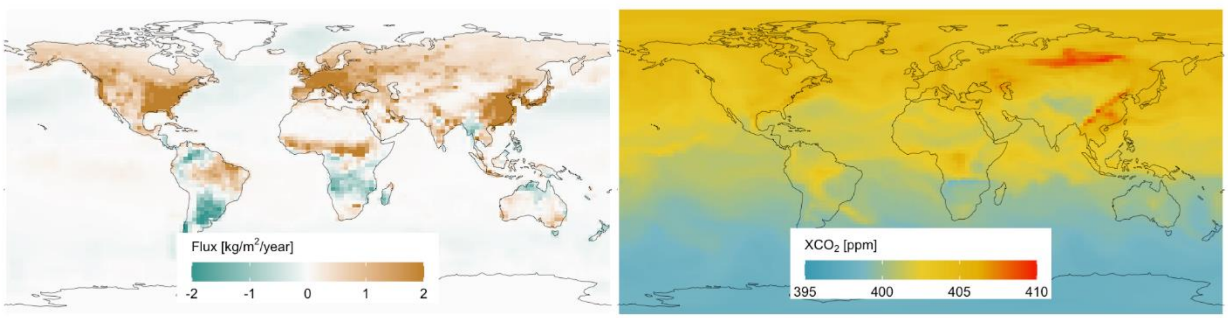

Figure 2: Left panel: Fluxes (in kilograms of CO_2 per square metre per year) for December 2015. Right panel: CO_2 concentrations (in parts per million) for a 3-hour period on 1 January 2016.

WOMBAT's CO_2 flux-inversion framework consists of a hierarchy of layers, similar in idea to the hierarchy of Russian nesting dolls, such as those shown in Image 2.

Image 2: Russian nesting dolls. [Photo by Sofia Boulamrach]

Like an intricate, connected machine, the uncertainty in one layer of the hierarchy can affect the uncertainty and estimates in another layer through a series of conditional-probability models. The outermost layer, the layer we "see," is made up of the data itself (call it Z). Atmospheric CO_2 concentrations can be measured indirectly from remote-sensing measurements, with good global coverage, or directly from *in situ* parcels of air collected from the atmosphere, but with sparse global coverage. Each of these measurement techniques is subject to some level of error, which is accounted for statistically. The second layer of WOMBAT's hierarchy is the latent process of CO_2 concentrations across the globe (call it Y; an example is shown in the right panel of Figure 2). This layer is dynamic, as the gas moves around through atmospheric transport, and its concentrations are modified by fluxes (the third layer). A chemical transport model is used to simulate these dynamics, and uncertainty in the second layer comes from imperfect information about the winds and the physics of atmospheric mixing. The third layer is the latent CO_2 flux process across the globe (call it X; an example is shown in the left panel of Figure 2), and it is the target of all our efforts. Like many other physical processes, fluxes at times and locations that are close together are more alike than those far apart. WOMBAT models this spatio-temporal dependence statistically to obtain valid flux estimates as well as their uncertainties. The fourth and innermost layer of WOMBAT's hierarchy describes the scientific knowledge and assumptions about the set of parameters (call it θ) that inform and control each of the other layers. These four layers together define a hierarchy that is shown in Figure 3.

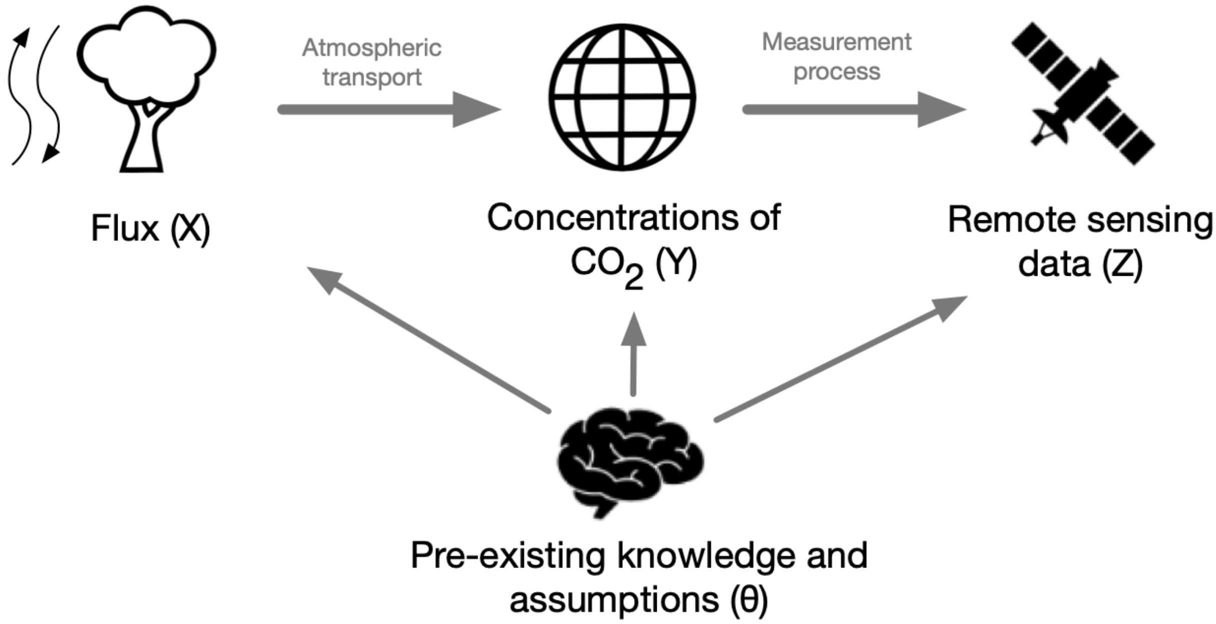

Figure 3: Diagram outlining WOMBAT's hierarchy of connected layers that incorporates atmospheric-concentration information from remote-sensing data, resulting in flux estimates and their uncertainties.

The layers are connected using conditional-probability models, as follows: Let *[A]* denote the probability distribution of variable *A; [A, B]* denote the joint probability distribution of the variables *A* and *B*; and *[A | B]* denote the conditional distribution of *A* given *B*. Using this notation, the four layers of WOMBAT are connected by the following probability distributions:

(1) $[Z \mid Y, \theta]$

(2) $[Y \mid X, \theta]$

(3) $[X \mid \theta]$

(4) $[\theta]$.

Bayes' Rule says that the posterior distribution, written as '*[unknowns | data]*', is proportional to '*[data | unknowns]*' x '*[unknowns]*'. That is, Bayes' Rule updates the prior, here written as '*[unknowns]*', using the likelihood, here written as '*[data | unknowns]*', to yield the posterior, here written as '*[unknowns | data]*'. In WOMBAT, *X*, *Y*, and θ are the unknowns, and *Z* is the data. Hence, from Bayes' Rule, the posterior distribution $[X, Y, \theta \mid Z]$ is proportional to (1) x (2) x (3) x (4).

What distinguishes WOMBAT from other flux inversions (e.g., those presented in Crowell et al., 2019) is the presence of (4) (i.e., the prior distribution, $[\theta]$) and the consequent **Markov Chain Monte Carlo (MCMC)** method used to obtain thousands of samples from $[X, Y, \theta \mid Z]$. WOMBAT's MCMC is necessarily complex given the very large quantities of data and unknowns (details can be found in Zammit-Mangion et al., 2022). Once the MCMC samples are obtained, estimates of CO_2 fluxes and uncertainties are obtained straightforwardly from $[X \mid Z]$ by extracting the posterior samples corresponding to the flux process *X*.

NASA's OCO-2 satellite data

Moving on from the simulation with our OSSE, we now present flux inversion through the eyes of WOMBAT, using remote-sensing data from the **Orbiting Carbon Observatory-2 (OCO-2)** satellite. Launched in July 2014 by the US National Aeronautics and Space Administration (NASA), it is NASA's first remote-sensing mission with primary science objective to understand the global geographic distribution of CO_2. Crisp et al. (2004) gives details on the remote-sensing instrument, which was designed to "ensure … space-based XCO_2 [i.e., column-averaged CO_2 concentration] measurements have precisions of ~0.3% (1 ppm) on regional scales." Atmospheric-concentration data from OCO-2 are available dating back to late 2014, and they cover much of each hemisphere, depending on the time of year. Because the instrument relies on reflected sunlight, it is not able to retrieve XCO_2 measurements in the higher latitudes during that hemisphere's winter months. Figure 4 shows an example of these data, representing the observations accumulated over the course of one week in January 2016 – notice that the satellite's orbital path can be seen in the spatial pattern of the observations. The analysis given here focuses on OCO-2 data (Version 7) for the two-year period from January 2015 to December 2016, which is the same data set featured in Crowell et al. (2019) and Zammit-Mangion et al. (2022).

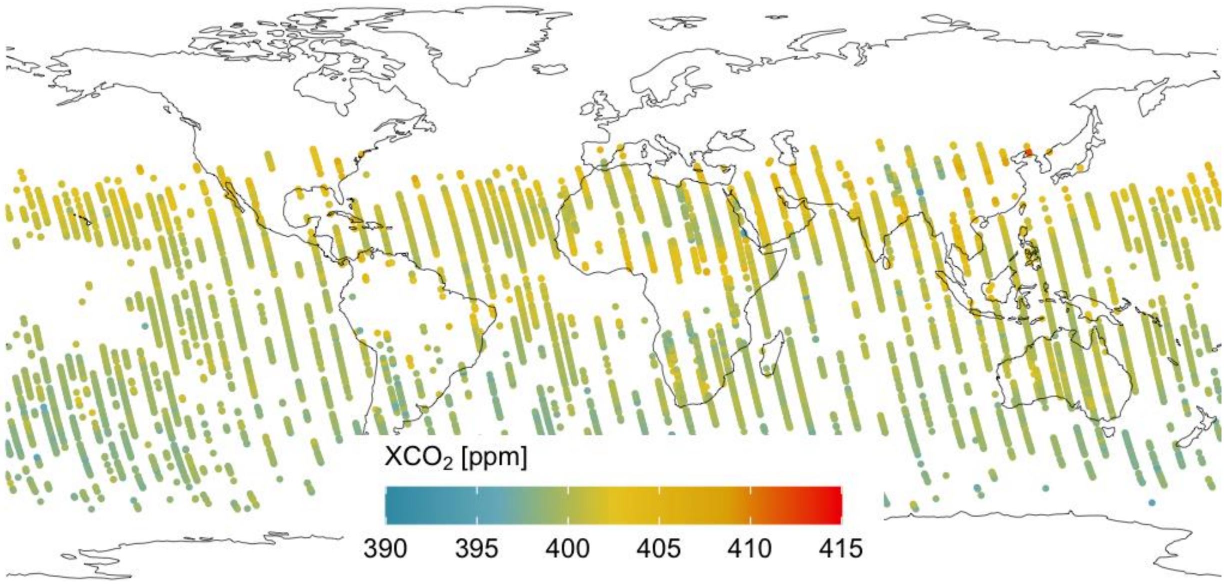

Figure 4: OCO-2 measurements of atmospheric column-averaged CO_2 concentrations (XCO_2, in ppm) from 1 January 2016 to 7 January 2016, inclusive.

Monthly estimated fluxes for 2015-2016

The CO_2 concentrations from *in situ* and satellite observations measure the downstream effect of the total fluxes. Because the fossil-fuel sources are well known, subtracting them from the flux-inversion estimate of total fluxes yields an estimate of the CO_2 natural fluxes. WOMBAT features spatio-temporal correlations in its latent-process model and measurement bias in its data model; the posterior distribution is obtained through MCMC, and its mean and variance gives estimated fluxes and uncertainties, respectively. Figure 5 shows these for the month of January 2016 across the globe. Fluxes were inferred for 2015 and 2016 from OCO-2 observations taken using an instrument mode called 'Land Glint' (LG). The left panel shows a map of the natural fluxes (posterior mean in each grid cell) in January 2016 over Earth's surface, in kilograms per metre squared per year. The right panel shows a map of the corresponding posterior standard deviation in each grid cell, which we use as a quantification of the uncertainties of the estimated fluxes shown in the left panel.

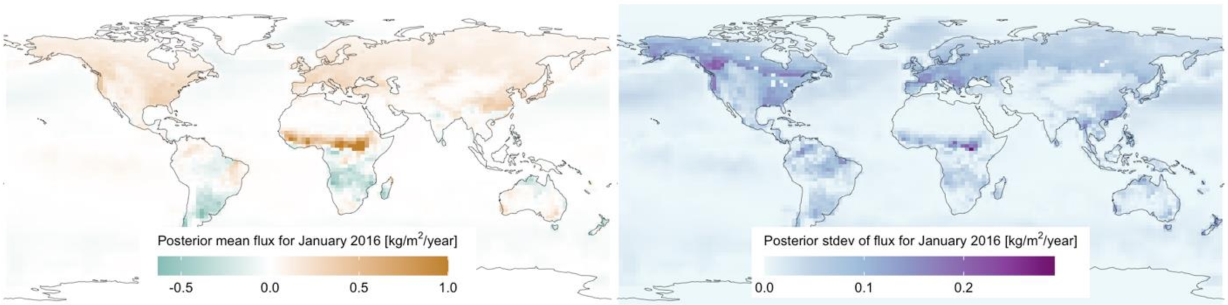

Figure 5: Left panel: Estimated monthly CO_2 natural fluxes (posterior mean) in January 2016. Right panel: Corresponding uncertainties (posterior standard deviation). Units are kg/m^2/year.

From studying all 24 monthly maps from January 2015 to December 2016, it can be seen that the tropics are relatively constant in their fluxes, while the temperate zones are very seasonal. This seasonal cycle of CO_2 is mostly driven by the vast forest areas in the Northern Hemisphere. Earth is breathing! In autumn and winter, trees drop their leaves, which decompose and release CO_2 into the atmosphere; in the spring and summer, leaves grow back and begin drawing down CO_2 through the process of photosynthesis; and the cycle repeats. Flux activity over the oceans is less intense at any given time and location but, because oceans cover two-thirds of Earth's surface area, the total contribution of the ocean fluxes is not negligible.

Figure 6 shows WOMBAT's yearly and monthly estimates of 'Global Land', 'Global Oceans', and 'Global' (the sum of the first two). It is seen that these largely agree with the flux estimates from the OCO-2 Model Intercomparison Project (MIP) described by Crowell et al. (2019), where nine groups performed flux inversion using the same data. Importantly, to quantify uncertainty the MIP relies on the variability of the nine estimates, whereas WOMBAT has an internally consistent quantification through the posterior variance. WOMBAT's estimate in the first row of Figure 6 shows that the combined effect of land and ocean fluxes leads to Earth's surface absorbing almost 4 Petagrams (4 billion tonnes) of carbon per year (PgC yr^{-1}). This sink is a yearly necessity, since humans are emitting almost 11 PgC yr^{-1} into the atmosphere (CarbonTracker, 2019). However, this yearly discrepancy means that CO_2 concentrations in the atmosphere will only keep increasing, baking in climate change until we decrease our sources and enhance our sinks.

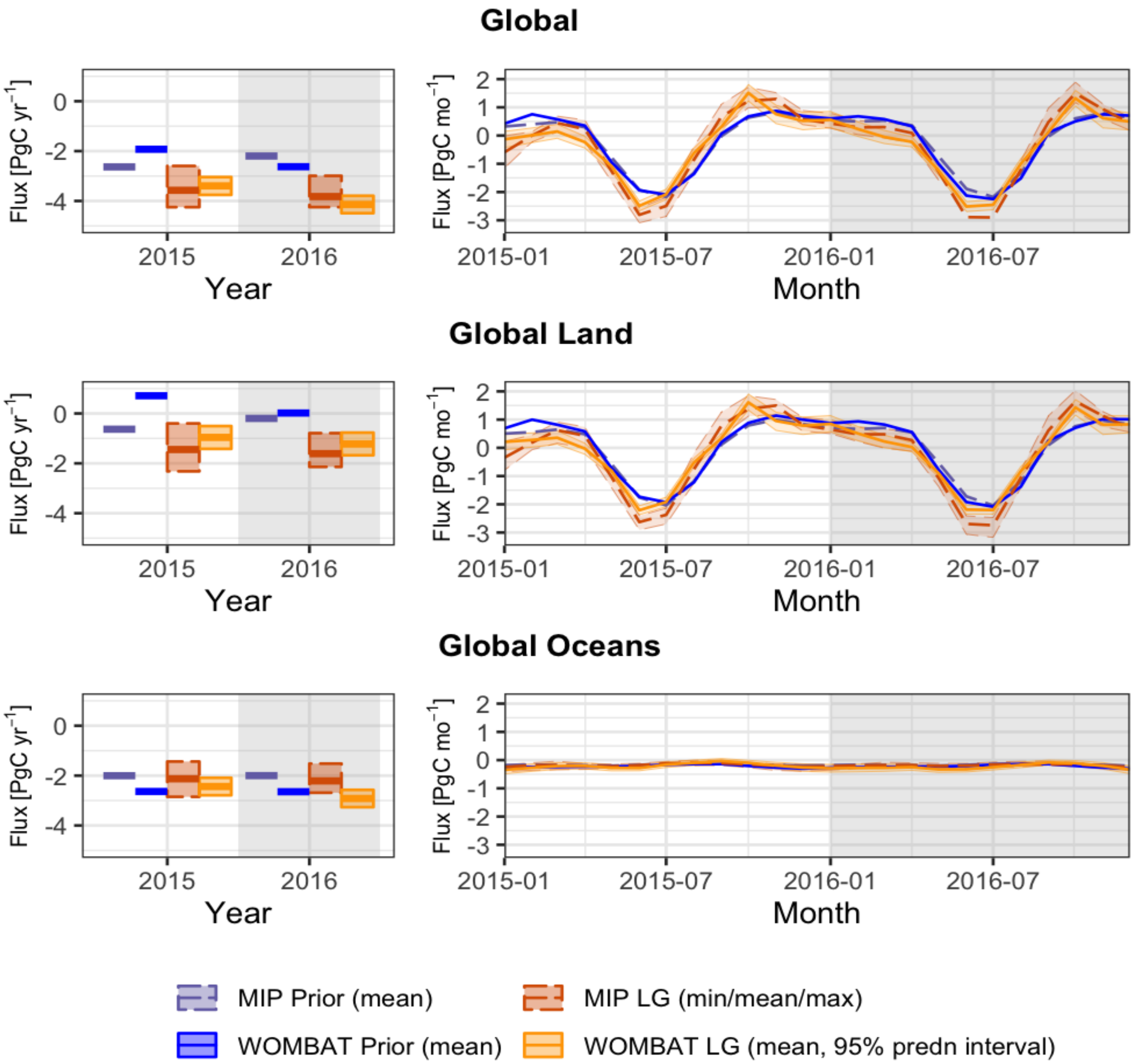

Figure 6: Annual (left column) and monthly (right column) CO_2 natural fluxes for the globe (first row), land (second row), and oceans (third row). The panels show the flux estimates and 95% prediction intervals from WOMBAT and summaries of flux estimates from the model intercomparison project (MIP), for OCO-2 Land Glint (LG) inversions. Also shown are WOMBAT's prior mean fluxes. [Figure modified from Zammit-Mangion et al. (2022)]

Conclusions and future work

To control and reduce the build-up of atmospheric CO_2 over the next century and uphold the urgent commitments of COP21 and later agreements, it is essential to understand where carbon is being exchanged with the atmosphere, how these regions vary through time, and whether there are ways to decrease the sources and enhance the sinks. As a framework for determining where CO_2 is emitted and absorbed across Earth's surface, and with its internally consistent uncertainty quantification, WOMBAT can separate out real signal from noise. To improve inferences from WOMBAT's BHM, there remain problems to solve: These include more flexible characterisation of the errors due to the chemical transport model, lower uncertainties for regional-scale, country-scale, or even finer-scale flux inversions, and an explicit modelling of the flux climatology.

In summary, separating the signal from the noise will help COP participants and policy makers reach consensus about greenhouse-gas stocktakes and make wise decisions about mitigation strategies. WOMBAT is specifically designed to aid scientists in evaluating the contribution of natural sinks to the CO_2 emission targets of countries and territories, and to understand their long-term viability. This may in turn lead to strategies that can replicate characteristics of CO_2 (and other greenhouse-gas) sinks over new regions of Earth's surface.

Acknowledgements

This article was supported by Australian Research Council (ARC) Discovery Project DP190100180 and NASA ROSES grants 17-OCO2-17-0012 and 20-OCOST20-0004. AZ-M was also supported by ARC Discovery Early Career Research Award DE180100203.

Disclosure Statement

The authors declare no competing interests.

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