# Understanding crop model response types in a global gridded crop model ensemble

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AgMIP The Agricultural Model Intercomparison and Improvement Project

## Background

Global Gridded Crop Models (GGCMs) are increasingly applied for assessing climate change impacts, adaptation, environmental impacts of agricultural production. In combination with integrated assessment or economic modeling they deliver data for projecting future land-use change. Even though global gridded crop models are often based on detailed field-scale models or have implemented similar modeling principles in other ecosystem models, global-scale models are subject to substantial uncertainties from both model structure and parametrization as well as from calibration and input data quality (Müller et al. 2017). AgMIP's Global Gridded Crop Model Intercomparison (GGCMI) has thus set out to intercompare GGCMs in order to evaluate model performance, describe model uncertainties, identify inconsistencies within the ensemble and (ideally) underlying reasons, and to ultimately improve models and modeling capacities (Elliott et al. 2015).

## The CTWN-A Experiment

The **CTWN-A** data cube: Regular disturbances of 31-year AgMERRA

- **C**: 360, 510, 660, 810 ppm ($n_C$=4)
- **T**: -1°C to +6°C, skipping 5°C ($n_T$=7)
- **W**: -50 to +30, skipping -40 + fully irrigated ($n_W$=9)
- **N**: 10, 60, 200 kgN/ha ($n_N$=3)
- **A**: regain lost growing season under warming (yes/no)
- 12 GGCMs participated, for up to 5 crops with up to 1404 global 30-year simulations, 7 primary output variables
- 4 GGCMs contributed with small samples only (<100 simulations) and are ignored here (APSIM-UGOE, EPIC-IIASA, ORCHIDEE-crop) for the others, gaps in the data sample (by protocol design (e.g. skipping T=5) or submitting less-dense data samples), have been filled with the GGCM-specific CTNW crop yield emulators (Franke et al., submitted).

**>20.000 global simulation time series**
**>400 million spatially explicit time series**
**>12 billion data points**

## Impact Response Surfaces and Response types

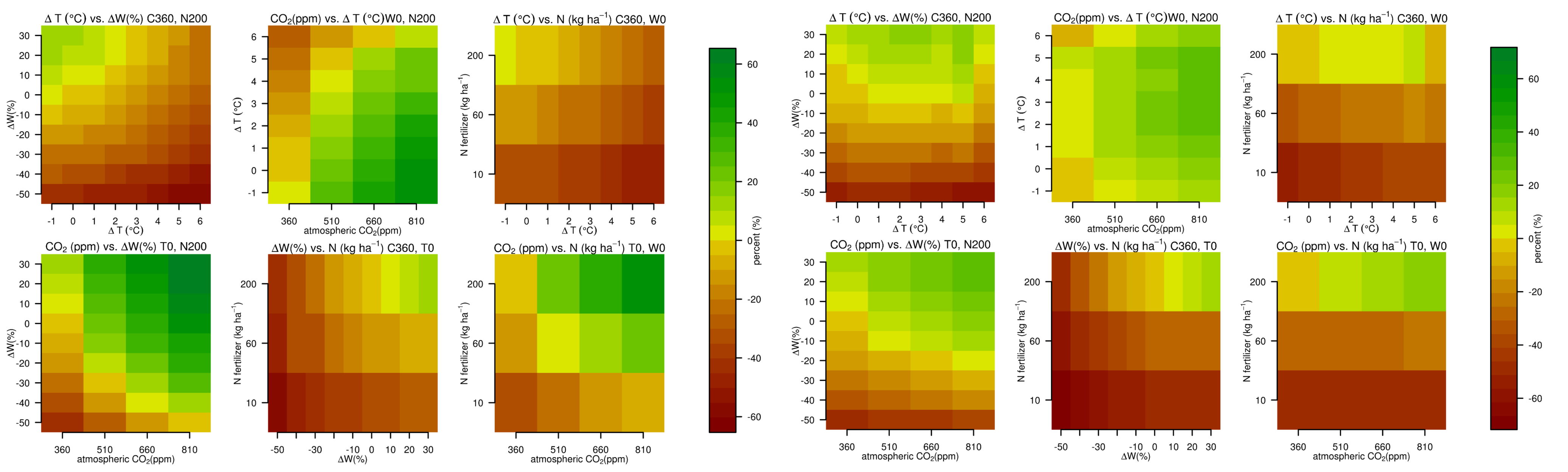


Fig. 1: In the 4-dimensional CTWN space, model responses can be described with 6 impact response surfaces (IRS). Examples for winter wheat simulations of LPJmL (left) and pDSSAT (right) at global-scale aggregation. All changes relative to C360, T0, W0, N200.

$$R_T = \frac{\sum_{i=1}^{nW} \max(\Delta y_i) - \min(\Delta y_i)}{nW}$$

$$R_W = \frac{\sum_{i=1}^{nT} \max(\Delta y_i) - \min(\Delta y_i)}{nT}$$

$$RR = {}^{R_T}/_{(R_W+R_T)}$$

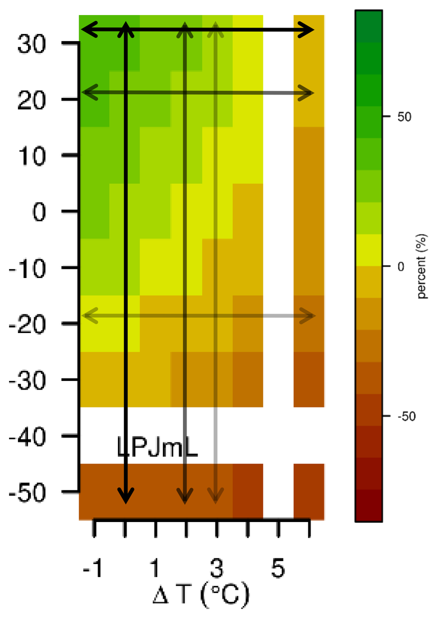



Fig. 2: For each IRS, the response ratio (RR) is computed as the average distance between the smallest and largest values (percent changes to baseline).

To avoid huge relative changes, response ratios are defined relative to the sum of the response in both dimensions ($R_T$ and $R_W$ in this example). A balanced sensitivity in both directions is thus represented by the value RR=0.5, no sensitivity to T relative to W by RR=0 and no sensitivity to W relative to T by RR=1.

The response ratio can be computed at global-scale aggregation or for each 0.5° grid cell.

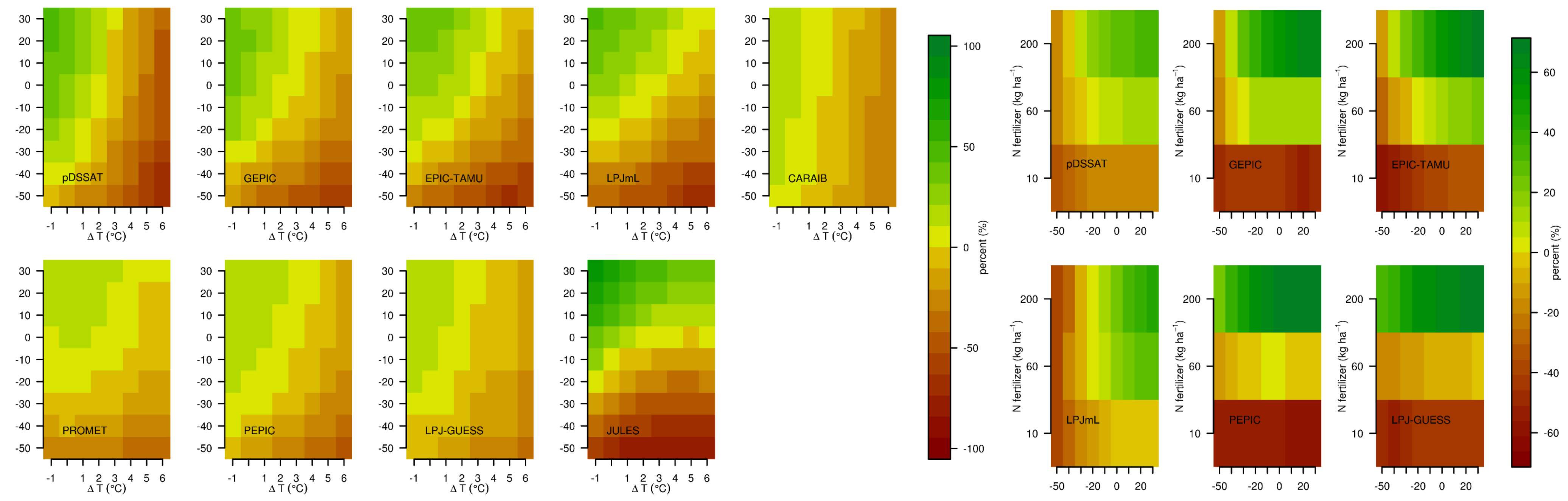
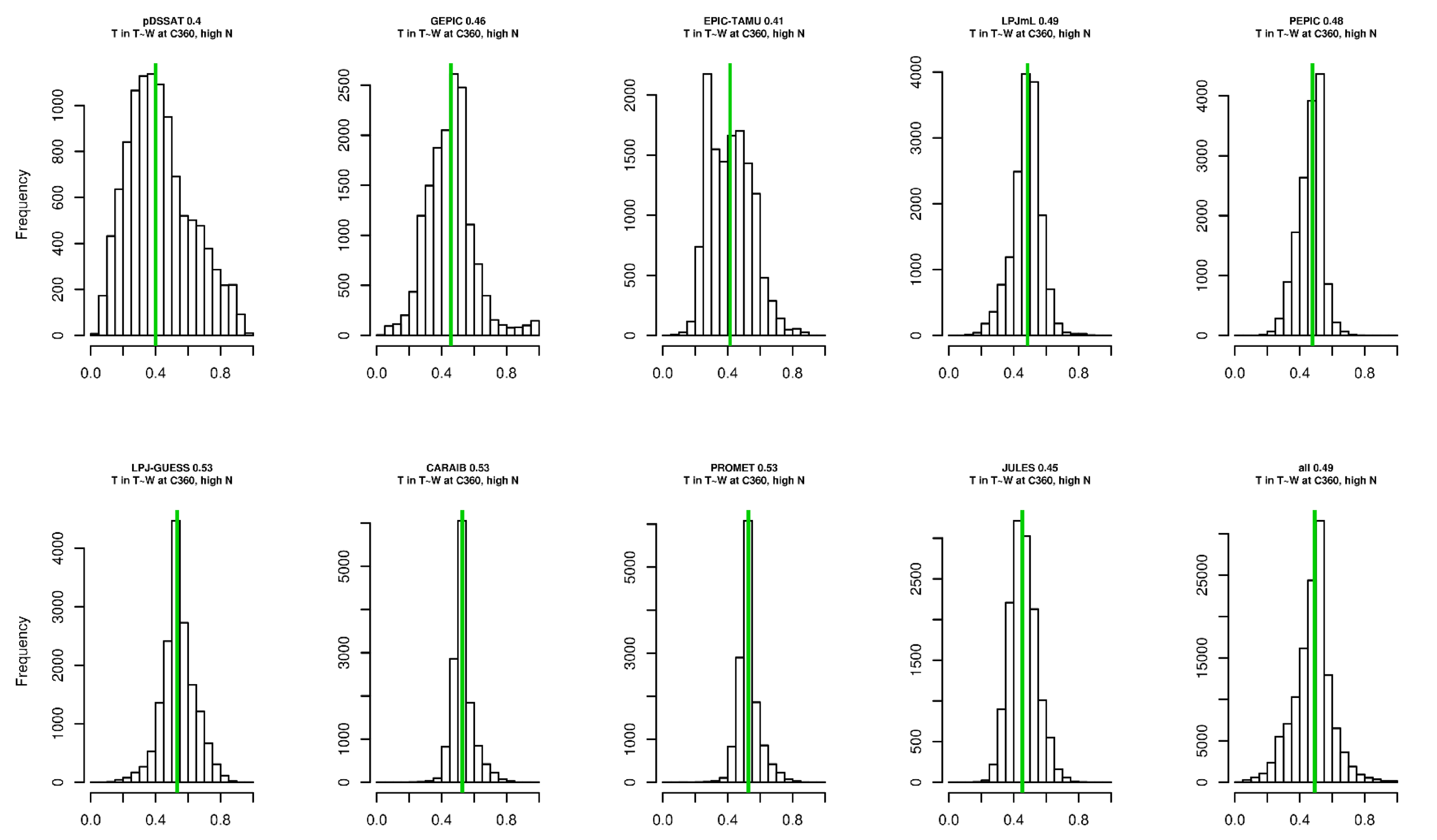



Fig. 3: IRS differ by model as shown for the T vs. W IRS (left) and the W vs. N (right) for maize. Not all GGCMs are capable of computing crop yields at different N levels and are thus excluded in the right panel. For example, PEPIC has a approximately balance sensitivity to changes in T and W (left panel) but little sensitivity to changes in W compared to changes in N (right panel), whereas LPJmL is more balanced in both IRS.

Fig. 4 (right): Distribution and median (green lines) response ratios (RR) in the T vs. W IRS for spring wheat. Models differ in their median sensitivity and the distribution. pDSSAT has the lowest sensitivity to changes in T relative to W (median of 0.40) and also the widest distribution; LPJ-GUESS, CARAIB, and PROMET have the highest sensitivity (median of 0.53). A value of 0.5 indicates balanced sensitivity to changes in T and W across the T *x* W IRS.



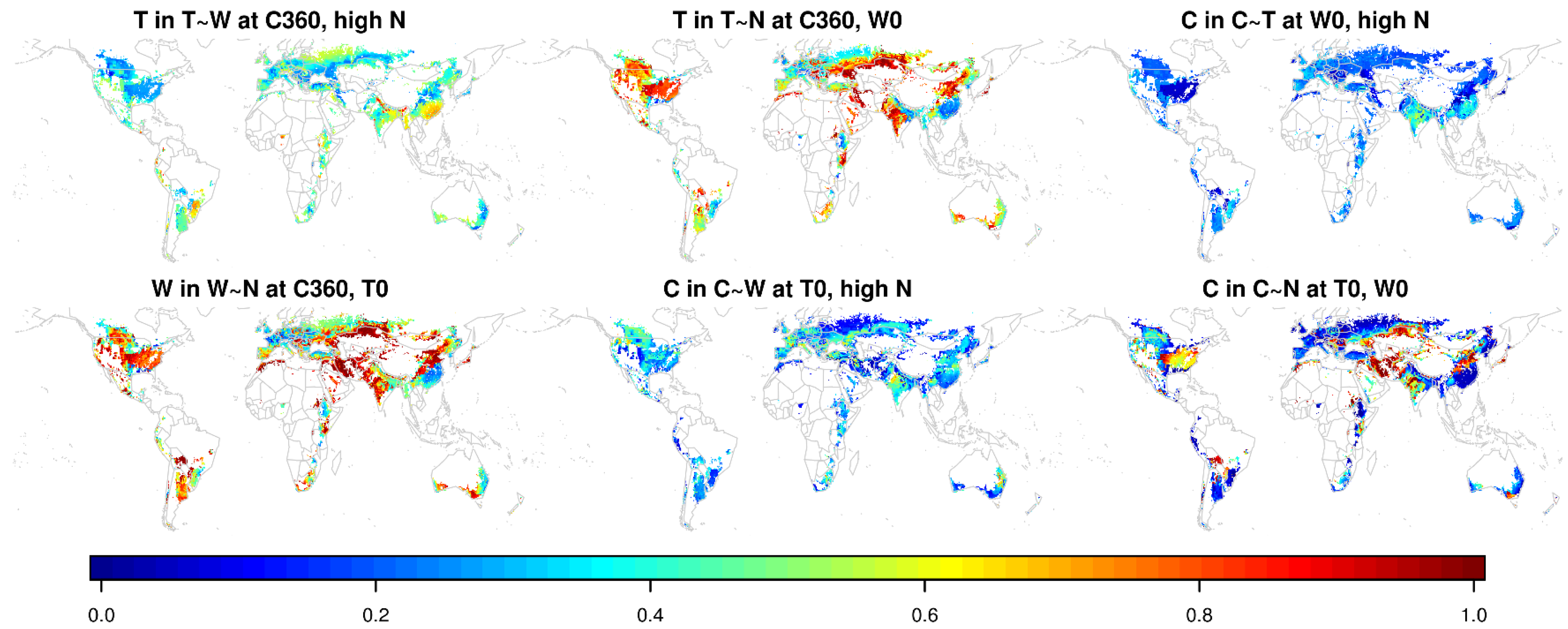



Fig. 5: Spatial patterns of spring wheat response ratios (RRs) for EPIC-TAMU for the 6 IRS in the CTWN space. Yields are less sensitive to changes in C compared to changes in T in all regions (at W0 and N200; top right) but can be more sensitive to changes in C than to changes in N in some regions (bottom right).

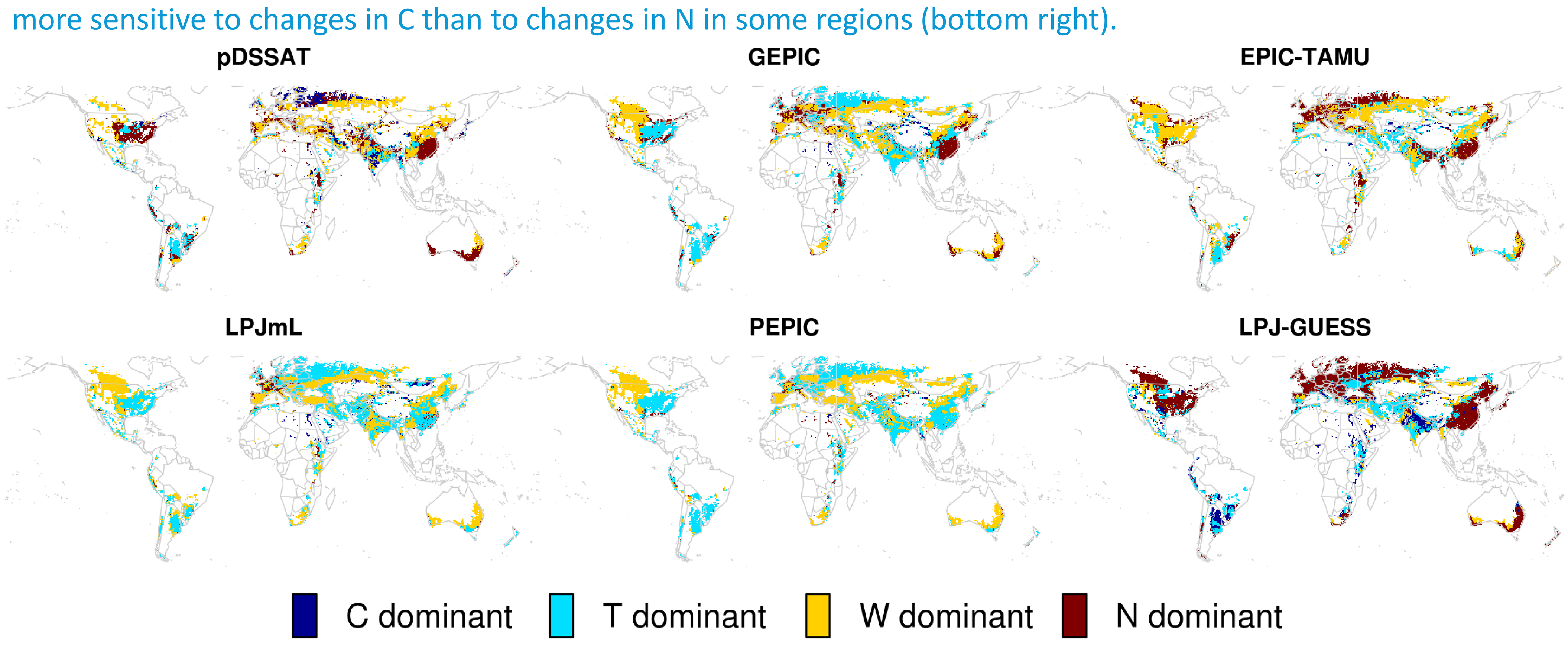



Fig. 6: Different GGCMs show distinct spatial patterns in the dominant response dimension (CTWN). GEPIC, LPJmL, and PEPIC show very good agreement in spatial patterns and dominant change dimensions. LPJ-GUESS is most sensitive to changes in N and has hardly any dominant sensitivity to changes in the W dimension. Maps show patterns for spring wheat.

## Conclusion and outlook

The output data ensemble of the GGCMI CTWN-A simulations is an unprecedentedly rich data base for agricultural analyses with global coverage. Data allow for emulation of model responses (Franke et al. submitted) for application in e.g. IAMs and gap filling. With these data we can distinguish response types in models as well as regions, understanding regional patterns of crop sensitivities to changes in climate. Even though the range of disturbances in the different dimensions are not directly comparable, the structured, protocol-based analysis allows for identifying regional and general model differences that can help to further identify reasons for model disagreement.

The GGCMI CTWN-A data set has been little explored so far. Beyond output data on crop yields, there are several other variables that allow for analyses much beyond what is shown here. Some work is ongoing but more can be done. If interested, please get in touch.

## References

Elliott et al. (2015): The Global Gridded Crop Model intercomparison: data and modeling protocols for Phase 1 (v1.0). Geosci. Model Dev. 8, 261-277, doi:10.5194/gmd-8-261-2015

Franke et al. (submitted to Geosci. Model Dev.): The GGCMI Phase II experiment: simulating and emulating global crop yield responses to changes in $CO_2$, temperature, water, and nitrogen levels

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