Signs of climate variability in double tropopause global distribution from two decades of radio occultation data

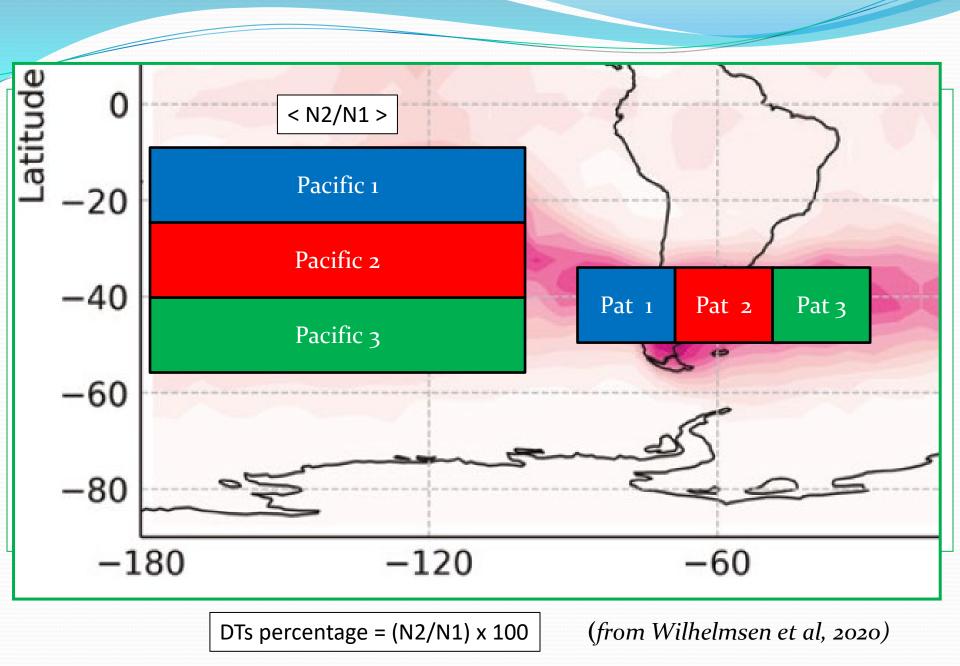
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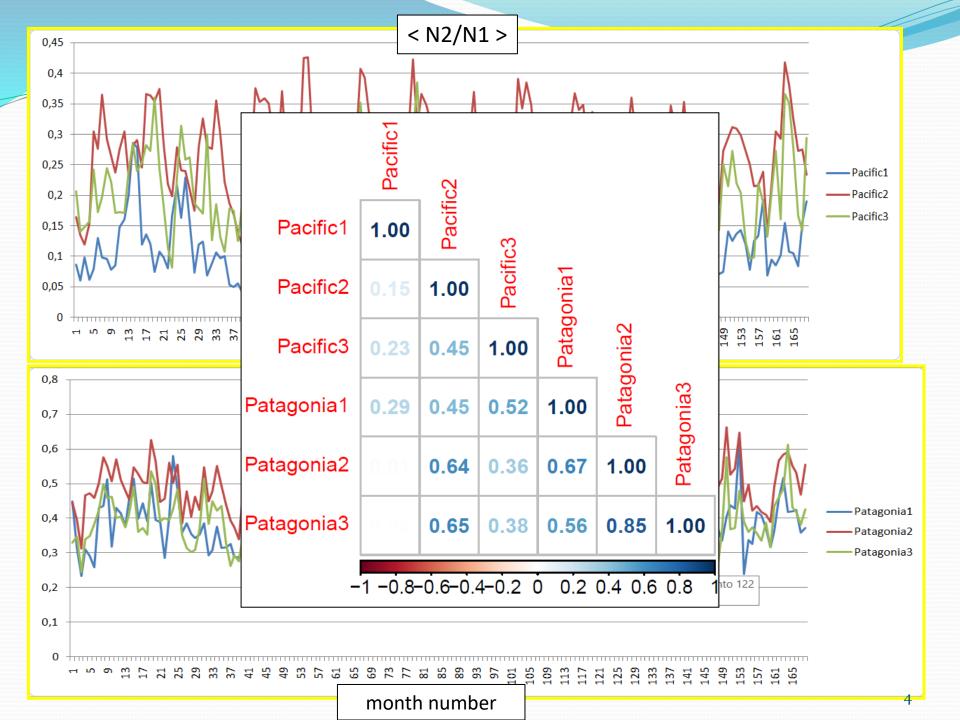
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Some previous knowledge

- vertical folding of the tropopause, occurrence of DTs
- midlatitudes (Peevey et al., 2014; Wang & Polvani, 2011, Homeyer et al., 2010; Castanheira et al., 2012; Liu & Barnes, 2018; Pan et al., 2009; Randel et al., 2007)
- storm track regions, subtropical jet stream (Bischoff et al., 2007; Schmidt et al., 2006; Seidel & Randel, 2006)
- mountain gravity waves (Schmidt et al., 2006) and
- cyclogenesis (Añel et al., 2008)
- Brewer-Dobson circulation (Castanheira et al., 2012)
- cloud-top inversion layers (Biondi et al., 2012)
- radiosonde measurements
- RO data (e.g. Randel et al., 2007; Schmidt et al., 2006; Xu et al., 2014) including the relationship to ENSO events (Wilhelmsen et al JGR 2020)





A preliminary work:

As an approximation to relate a meteorological signal using different indices,

Llamedo et al., 2016 (after Randel & Wu, 2015 and other relevant contributions)

ENSO, PW, q and T

$$\begin{split} F\left(t\right) = A_0 + A_1 t + A_2 sin\left(\omega t\right) + A_3 cos\left(\omega t\right) + A_4 sin\left(2\omega t\right) \\ + A_5 sin\left(2\omega t\right) + A_6 sin\left(3\omega t\right) \\ + A_7 cos\left(3\omega t\right) + B_1 \text{QBO1}\left(t\right) \\ + B_2 \text{QBO2}\left(t\right) + B_3 \text{SF}\left(t\right) \end{split}$$

Multiple linear regression

A multiple regression model is written as

 $egin{aligned} y_i &= eta_0 + \sum_{j=1}^d x_{ij}eta_j + \epsilon_i \ &= eta_0 + eta_1 x_{1i} + eta_2 x_{2i} + \ldots + eta_d x_{di} + \epsilon_i, \quad i=1,2,\ldots n \end{aligned}$

The β coefficients are obtained by minimizing the residual sum of squares, thus obtaining:

$$\hat{eta} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y}$$

psl.noaa.gov/data/climateindices/list

Given new data X_{new}, the least squares prediction is:

$$\hat{y} = \mathbf{X}_{new} \hat{eta} = \mathbf{X}_{new} (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y}$$

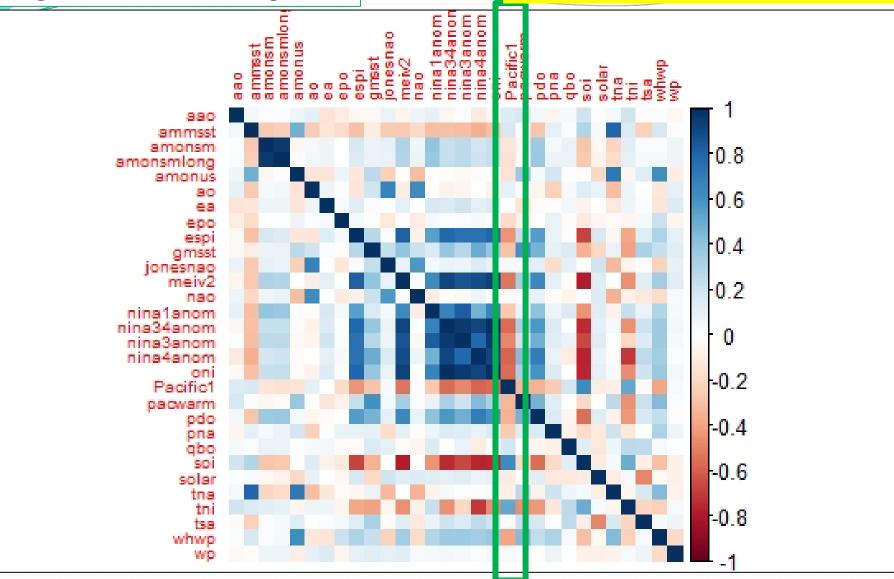
Climate indices from :

$$RMSE = \sqrt{rac{\sum_{i=1}^n (pred_i - obs_i)^2}{n}}$$

Root Mean Squared Error

e.g.: Pacific 1 subregion

Climate indices from : psl.noaa.gov/data/climateindices/list



Correlations with R² > 0.5 is found between the response variable and predictors: "meiv2", "nina34anom", "nina4anom", "oni", "soi", "tni"

Considering only these latter "best" predictors ("meiv2", "nina34anom", "nina4anom", "oni", "soi", "tni") for "Pacific1":

meiv2 0.4 0.3 0.2 0.1	nina34anom Corr: 0.915***	nina4anom Corr: 0.881***	∝ Corr: 0.924***	soi Corr: -0.786***	™ Corr: -0.457***	Pacific1 COTT: -0.534***	mely2
0.0 2 1 0 -1	\bigwedge	Corr: 0.912***	Corr: 0.997***	Corr: -0.746***	Corr: -0.458***	Corr: -0.564***	nina34anom
		\frown	Corr: 0.917***	Corr: -0.761***	Corr: -0.701***	Corr: -0.586***	nina4anom
2 1 0 -1	/	and the second second	\sim	Corr: -0.756***	Corr: -0.464***	Corr: -0.566***	8
2.5 0.0 -2.5	Wildow.		Sec.	$ \land $	Corr: 0.492***	Corr: 0.621***	50
2 0 -2 0.3					\wedge	Corr: 0.510***	2
0.2 0.1 -2 -1 0 1 2	-1 0 1 2	1 0 1	4 0 1 2	-2.5 0.0 2.5 5.0	-2 0 2		Pacific1

Three regression models to predict DTs from different sets of arbitrary predictors were compared:

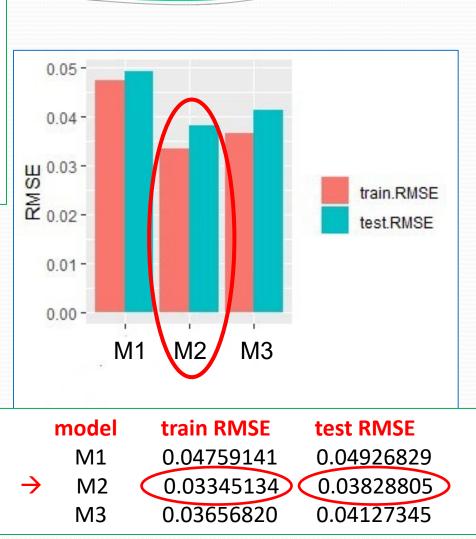
M1) "baseline" (only β_0) **M2**) $\beta_0 + \beta_1 \text{soi} + \beta_2 \text{ whwp} + \beta_3 \text{tni} + \beta_4 \text{ oni}$ **M3**) "linear" ($\beta_0 + \beta_1$ soi)

As an example, for M2:

Residuals: 10 Min Median 30 -0.0677 -0.0234 -0.0030 0.0171 0.1009

Max

Coefficients: Estimate Std. Error t value (Intercept) 0.118982 0.004959 23.993 0.011925 0.003033 3.931 soi whwp -0.004230 0.001483 -2.852 -0.005017 0.005591 -0.897 oni 0.007947 0.002397 3.316 tni



Summary

- 5 sub-regions (Pacific 2-3 and Patagonia 1-2-3) show a correlation between their respective monthly averaged TDs
- DTs in *Pacific 1* (to the north of the subtropical jet) exhibit a different behavior
- However, it correlates better with the global indices than the other 5 subregions do
- Progressive addition of global indices to the model improves its performance, reducing the RMSE of training and testing.

Current work

- A possible correlation between the observed distribution of DTs (from RO) and inertio gravity waves, usually radiated by geostrophic adjustment near to the subtropical jet (predictor proposed: cross-current Rossby number) is being analyzed.
- A principal component study is being performed on the available 20-year DTs dataset and 5x5 lat/lon deg pixels in the southern hemisphere.

Thank you for your attention

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