

Supplementary Information for

Network-based Forecasting of Climate Phenomena

Josef Ludescher, Maria Martin, Niklas Boers, Armin Bunde, Catrin Ciemer, Jingfang Fan, Shlomo Havlin, Marlene Kretschmer, Jürgen Kurths, Jakob Runge, Veronika Stolbova, Elena Surovyatkina, Hans Joachim Schellnhuber

E-mail: josef.ludescher@pik-potsdam.de or maria.martin@pik-potsdam.de

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Fig. S1 Table S1 SI References



Fig. S1. Results of the network analysis and propagation of extreme rainfall from southeastern South America to the eastern Central Andes. The figure shows the network divergence of a directed and weighted network constructed from 3-hourly rainfall events above the 99th percentile. The network divergence is defined as the difference of in-strength and out-strength at each grid cell, $\Delta S_i = S_i^{in} - S_o^{out}$, where the in- and out-strengths at each node are themselves given by the sums of all network weights assigned to directed links leading into and out of that node. Positive values thus indicate sinks of the directed and weighted network, which are interpreted as locations where synchronized extreme rainfall occurs within 2 days after it occurred at several other locations. Negative values indicate sources, that is, locations where synchronized rainfall occurs within 2 days before it occurs at several other locations. The boxes labelled 1 to 7 track the path of the extreme events from southeastern South America toward the Central Andes. Figure adapted with permission from ref. (4), copyright 2014 Nature Publishing Group.

| Phenomenon | Network Forecast | Comparable state-of-the-art | Similar state-of-the-art oper- |
|---------------|-------------------------------|-----------------------------|--------------------------------|
| | | operational forecast | ational forecast |
| El Niño onset | 73% of El Niño onsets and | No comparable 12 months | Forecasts for Nov-Jan pro- |
| | 89% of their absences were | ahead forecast available. | vide less than 10% explained |
| | correctly hindcasted or fore- | | variance when initiated in |
| | casted in the calendar year | | February and more than 80% |
| | before. Mean lead time be- | | when initiated in September |

Table S1. Comparison between network-based forecasts and comparable or similar state-of-the-art operational forecasts, to the best of our knowledge.

| | | | J |
|-------------------------------|--------------------------------|---------------------------------|----------------------------------|
| | before. Mean lead time be- | | when initiated in September |
| | fore an El Niño onset is 12 | | of the same year (2) . |
| | months (1) . | | |
| Droughts in the Central | Six out of the seven most se- | No prior attempt to fore- | Same as left. |
| Amazon | vere droughts in the last four | cast this specific climate phe- | |
| | decades were hindcasted at | nomenon. | |
| | lead times of 12 to 18 months | | |
| | (3). | | |
| Extreme Rainfall in the east- | Up to 2 days lead time | No prior attempt to fore- | Same as left. |
| ern Central Andes | for correctly forecasting 60% | cast this specific climate phe- | |
| | (90% during El Niño condi- | nomenon. | |
| | tions) of the extreme rainfall | | |
| | events (4). | | |
| Indian summer monsoon on- | 73% (84%) correct onset | No dedicated long-term fore- | Two weeks in advance on- |
| set and withdrawal | (withdrawal) hindcasts for | cast for Central India, stan- | set forecast for Kerala in |
| | Central India for 1965-2015 | dard weather forecast of | South India, no dedicated |
| | (5). All forward-looking on- | about 5 days (7) . | withdrawal date forecast (7) . |
| | set (withdrawal) forecasts | | |
| | with 40 (70) days lead time | | |
| | were correct for 2016-2020 | | |
| | (6). | | |
| Extreme stratospheric polar | Predictive skill up to 45 | No prior attempt to forecast | Predictability up to 30 days |
| vortex states | days for extreme 15-day- | a 15-day-mean of the SPV. | for daily events, but strongly |
| | mean events (8) | | varying for individual events |
| | | | and usually much shorter |
| | | | (9). |

References

- 1. J. Ludescher *et al.*, Improved El Niño forecasting by cooperativity detection. *Proc. Natl. Acad. Sci. USA* **110**, 11742-11745 (2013).
- 2. NOAA climate.gov. https://www.climate.gov/news-features/blogs/enso/spring-predictability-barrier-we%E2%80%99d-rather-be-spring-break. Accessed February 12 2021.
- 3. C. Ciemer *et al.*, An early-warning indicator for Amazon droughts exclusively based on tropical Atlantic sea surface temperatures. *Environmental Research Letters* **15**, 9, 094087, https://doi.org/10.1088/1748-9326/ab9cff (2020).
- 4. N. Boers *et al.*, Prediction of extreme floods in the eastern Central Andes based on a complex networks approach. *Nature Commun.* **5**, 5199 doi: 10.1038/ncomms6199 (2014).
- 5. V. Stolbova, E. Surovyatkina, B. Bookhagen, J. Kurths, Tipping elements of the Indian monsoon: Prediction of onset and withdrawal. *Geophys. Res. Lett.* **43**, 8, 3982-3990 (2016).
- Potsdam Institute for Climate Impact Research, Monsoon Page. https://www.pik-potsdam.de/services/infodesk/forecastingindian-monsoon. Accessed July 31 2020.
- 7. D. S. Pai, R. M. Nair, Summer monsoon onset over Kerala: new definition and prediction. J. Earth Syst. Sci. 118, 123-135 (2009).
- 8. M. Kretschmer, J. Runge, D. Coumou, Early prediction of extreme stratospheric polar vortex states based on causal precursors. *Geophys. Res. Lett.* 44, 16, 8592-8600 (2017).
- 9. D. I. Domeisen *et al.*, The role of the stratosphere in subseasonal to seasonal prediction Part I: Predictability of the stratosphere. J. Geophys. Res. Atmos., **125**, e2019JD030920 (2020).