# Global terrestrial ecosystem resilience: a high-resolution multivariate analysis of patterns and drivers

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## 1. Background: Detection of ecosystem resilience losses

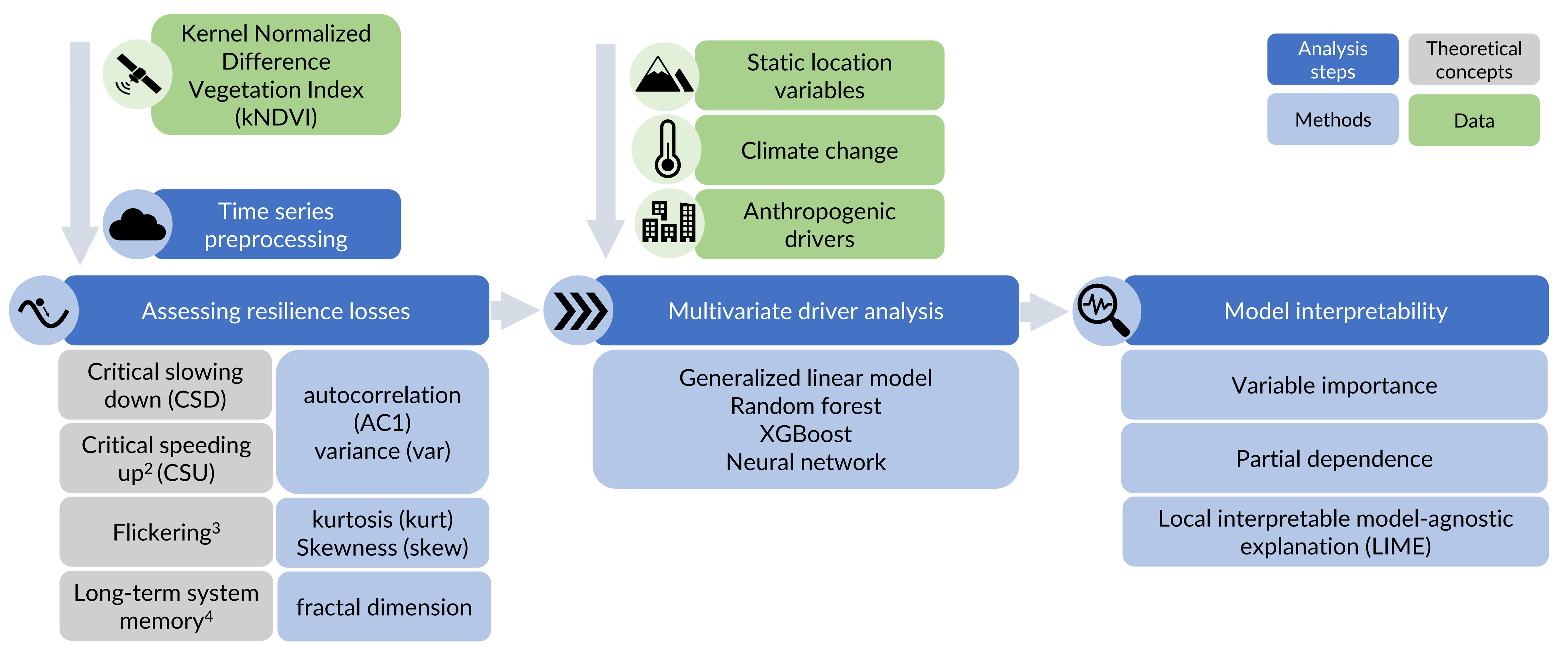
Ecosystems around the world are under increasing pressure from multiple climatic and anthropogenic drivers. These can push ecosystems towards new, often unwanted states through regime shifts. Regime shifts can occur gradually or abruptly, through incremental linear changes, or stochastic fluctuations in drivers but also via increased sensitivity to external shocks. They are often predated by frequently unrecognized resilience losses[1].

To improve **detection of resilience losses and understanding of drivers**, it is therefore crucial to account for the multivariate, non-linear nature of the observed ecosystems. Most traditional early warning signals (EWS) of resilience losses, however, are based on assumptions made for univariate systems.

Our aim is to get a **comprehensive, multivariate understanding of resilience losses** in global terrestrial ecosystems and their drivers, using vegetation indices from remote sensing data with a range of different EWS based on different mechanistic assumptions and machine learning models.
We aim to answer two main questions:

1. **What are the spatial patterns of resilience loss in terrestrial ecosystems as assessed with different EWS?**
2. **What are the relevant climatic and anthropogenic drivers of these resilience losses on global and local level?**

## 2. Methods: The analysis pipeline




## 3. Preliminary results: Patterns and drivers of resilience losses

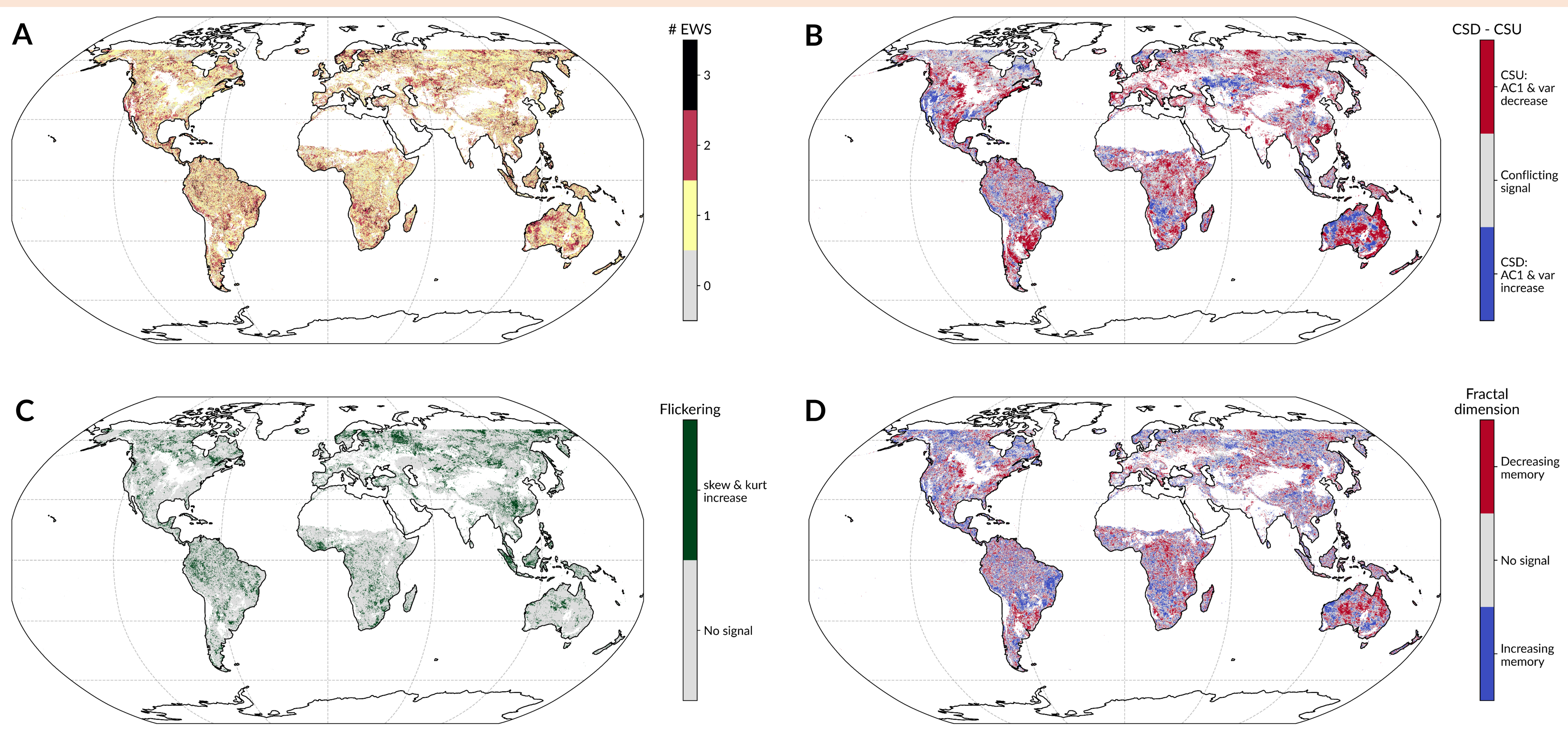



Fig. A – D: Maps of different early warning signals detected over the period from 2000 – 2023. **A)** ***Total number of EWS*** showing a warning signal. **B)** ***Critical Slowing Down (CSD)*** and ***Critical Speeding Up (CSU)*** as defined where AC1 and variance both show a positive or negative trend, respectively. **C)** ***Flickering***, where both skewness and kurtosis show an increasing positive trend, **D)** ***Long term memory***, as defined as pixels where the fractal dimension shows a significant decrease (increasing long term memory) or increase (decreasing long term memory).

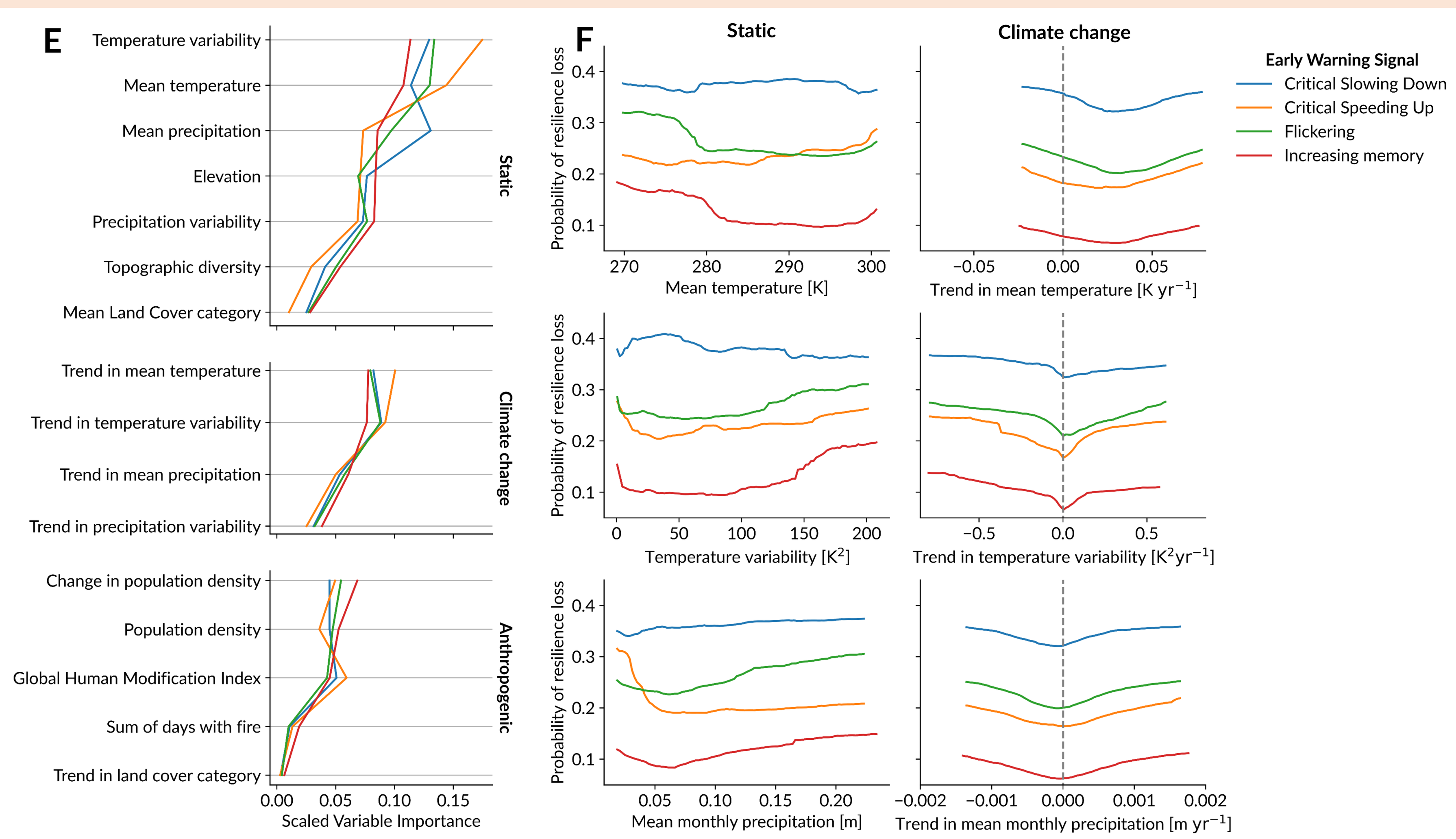



Fig. E – F: Model interpretability analyses for the *Random Forest driver models*. **E)** ***Variable importance*** based on permutation assessed for the models for four different EWS, scaled to sum to 1 for each EWS.
**F)** ***Selected partial dependency plots*** showing the mean predicted value for the range of each predictor, while keeping the values of all other predictors constant at their mean value.

## 4. Discussion: What do we find?

**How do geographic patterns of resilience loss compare between EWS indicators?**

- **Resilience loss patterns are generally patchy**, but show spatial clustering in specific regions, such as across Russia and central Asia, the western US, Northeastern Brazil, the western Amazon, and western Australia.
- In **large tropical forests**, resilience loss patterns show small scale, noisy variations, which is in agreement with previous work using different approaches[5, 6].
- **Different EWS pick up signals in different patterns**. The ***fractal dimension*** shows similar warning signals as the ***CSD-CSU*** patterns, with deviations mostly in the high latitudes. ***Flickering***, on the other hand, seems to be associated with the boundaries between biomes, which might indicate shifting climatic conditions in regions of strong environmental gradients.

**What role do different drivers play in determining signs of resilience loss?**

- For all EWS, **static environmental variables** are the strongest predictors in the driver models showing that sensitivity of different ecosystems to pressures is strongly determined by their biogeographic zone, which agrees with previous work[7].
- Both **negative and positive changes in temperature and precipitation** (mean and variance) lead to resilience losses. However, for moderate temperature increases (up to ~0.2-0.3°C/decade), the likelihood of resilience losses decreases. This might be associated with a $CO_2$ fertilization effect that is cancelled out at higher increases[5].

**How do drivers compare with respect to CSD, CSU, flickering and long term memory?**

- ***CSD occurrence*** is most strongly determined by change of mean monthly precipitation, with dry ecosystems showing highest resilience losses. This agrees with patterns found in local and global studies previously[8, 9].
- ***CSU patterns***, contrarily, are determined more by mean temperature and temperature variability.
- ***Flickering*** and increasing ***long-term memory*** occur more frequently in colder, high latitude ecosystems with high temperature variability. This is also where AC1 and variance often show conflicting signals[6] and can be a sign that there are still complex resilience losses ongoing.

**Next questions…**

- How are resilience losses in the water cycle connected to these patterns in terrestrial ecosystems?
- What can spatial EWS tell us about terrestrial resilience losses?
- What is the role of fast and slow dynamics of climate change drivers for the different EWS (e.g. intra-annual vs inter-annual variability)?

## References

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## Want to connect?

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