**Supplementary Materials**

**S.1. Further Background on Transfer Entropy (TE)**

TE is expressed as a specific version of Kullback-Leibler divergence [1] i.e., the relative entropy [2]:

$$TE\left(X\rightarrow Y, μ\right)=\sum\_{y\_{t}, y\_{t-1}^{dy},x\_{t-μ}^{dx}}^{}p(y\_{t},y\_{t-1}^{dy},x\_{t-μ}^{dx})log\frac{p(y\_{t}|y\_{t-1}^{dy},x\_{t-μ}^{dx})}{p(y\_{t}|y\_{t-1}^{dy})}$$

where parameter $μ$ (referred to as delay embedding i.e., the lagged history) is the assumed time that the information transfer needs to get from X to Y and $y\_{t-1}^{dy}$ represents the past of Y. Similarly, $X\_{t-μ}^{dx}$ refers to the past of X while incorporating the delay embedding $μ$ (ibid). This equation quantifies the degree to which the history of X predicts the current state of Y beyond the degree to which Y could be predicted by its own history, or equivalently [3]:

$$TE\left(X\rightarrow Y\right)≡H\left(Y\_{n}^{μ}\right)-H\left(Y\_{n}^{μ},X\_{n}^{μ}\right)$$

where $H\left(Y\_{n}^{μ}\right) $and $H(Y\_{n}|Y\_{n}^{μ},X\_{n}^{μ})$ give conditional entropy of Y at time n given its $μ$-lag history and conditional entropy of Y at time n given its own and X’s $μ$-lag history.

In essence, TE quantifies the deviation from generalized Markov property $p(y\_{t+1}\left|y\_{t},x\_{t}\right)=p\left(y\_{t}\right),∀y\_{t},y\_{t+1}\in Y,x\_{t}\in X$, where $p(y|x)$ represents the probability of occurrence of $x$, given $y$ occurred. If this deviation is small, then the state of $X$ is assumed to have minimal or no relevance on the transition probabilities of $Y$ [4], thereby implying an absence and/or a non-significant effect of $X$ on $Y$.

It is worthy of note that unlike MI that measures correlation (i.e., a measure of synchrony while taking into account the linear and nonlinear relations), TE is explicitly and strictly non-symmetric under exchange of the role of the interacting processes [5]. In other words, $TE\left(X\rightarrow Y\right)\ne TE\left(Y\rightarrow X\right),∀X,Y$.

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