SUPPLEMENTARY MATERIALS

Quantifying Causal Contributions in Earth Systems by Normalized 5 Information Flow

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Fig. #	Interdependent function	Noise function (inc. self-dependency)
	One-Dimensional: nt = 2 to 3000; (or split into 2-1	1000, 1001-2000, 2001-3000)
initial conditions (i.e. nt = 1) are zeros;		
_{nt} or _{nt-1} refers to nt th or (nt-1) th term on time-axis		
2 & S1 - low noise	$\frac{\partial X 1_{Y1}}{\partial t}\Big _{nt} = \frac{\cos\left[\frac{\left(2nt + \sum_{2}^{nt} \frac{1}{nt}\right)}{120\pi}\right]}{1.1} \times \frac{dY1}{dt}\Big _{nt-1} + \frac{\sin\left[\frac{\left(2nt - \sum_{2}^{nt} \frac{1}{nt}\right)}{120\pi}\right]}{1.5} \times \frac{dY1}{dt}\Big _{nt-1} + \frac{1}{300} \frac{dY1}{dt}\Big _{nt-1}$	$\frac{\partial X 1_{noise}}{\partial t}\Big _{nt} = 0.00001 + \left \frac{\cos\left(\frac{4nt}{200\pi}\right)}{0.9}\right - \frac{X 1 _{nt-1}}{5000}$
	$\frac{\partial Y 1_{X1}}{\partial t}\Big _{nt} = \frac{\cos\left[\frac{\left(nt + \sum_{2}^{nt} \frac{1}{nt}\right)}{310\pi}\right]}{1.8} \times \frac{dX1}{dt}\Big _{nt-1} - \frac{\sin\left[\frac{\left(2nt - \sum_{2}^{nt} \frac{1}{nt}\right)}{240\pi}\right]}{2.5} \times \frac{dX1}{dt}\Big _{nt-1} + \frac{1}{500}\frac{dX1}{dt}\Big _{nt-1}$	$\frac{\partial Y 1_{noise}}{\partial t}\Big _{nt} = 0.000005 + \frac{\left \frac{\sin\left(\frac{2nt}{300\pi}\right)}{0.8}\right }{-\frac{Y1 _{nt-1}}{5000}}$
S4 - medium noise	$\frac{\partial X 1_{Y1}}{\partial t}\Big _{nt} = \frac{\cos\left[\frac{\left(2nt + \sum_{2}^{nt} \frac{1}{nt}\right)}{120\pi}\right]}{1.8} \times \frac{dY1}{dt}\Big _{nt-1} + \frac{\sin\left[\frac{\left(2nt - \sum_{2}^{nt} \frac{1}{nt}\right)}{120\pi}\right]}{2.5} \times \frac{dY1}{dt}\Big _{nt-1} + \frac{1}{500}\frac{dY1}{dt}\Big _{nt-1}$	$\frac{\partial X 1_{noise}}{\partial t}\Big _{nt} = 0.01 + \left \frac{\cos\left(\frac{4nt}{500\pi}\right)}{0.2}\right - \frac{X1 _{nt-1}}{5000}$
	$\left \frac{\partial Y 1_{X1}}{\partial t} \right _{nt} = \frac{\cos\left[\frac{\left(nt + \sum_{2}^{nt} \frac{1}{nt}\right)}{310\pi}\right]}{2.9} \times \frac{dX1}{dt} \Big _{nt-1} - \frac{\sin\left[\frac{\left(2nt - \sum_{2}^{nt} \frac{1}{nt}\right)}{240\pi}\right]}{3.9} \times \frac{dX1}{dt} \Big _{nt-1} + \frac{1}{700} \frac{dX1}{dt} \Big _{nt-1}$	$\frac{\partial Y1_{noise}}{\partial t}\Big _{nt} = 0.005 + \frac{\left \frac{\sin\left(\frac{2nt}{600\pi}\right)}{0.17}\right }{-\frac{Y1 _{nt-1}}{5000}}$
4 & S3 - strong noise	$\frac{\partial X 1_{Y1}}{\partial t}\Big _{nt} = \frac{\cos\left[\frac{\left(2nt + \sum_{2}^{nt} \frac{1}{nt}\right)}{120\pi}\right]}{1.8} \times \frac{dY1}{dt}\Big _{nt-1} + \frac{\sin\left[\frac{\left(2nt - \sum_{2}^{nt} \frac{1}{nt}\right)}{120\pi}\right]}{3.2} \times \frac{dY1}{dt}\Big _{nt-1} + \frac{1}{500}\frac{dY1}{dt}\Big _{nt-1}$	$\frac{\partial X1_{noise}}{\partial t}\Big _{nt} = 0.001 + \frac{\cos\left(\frac{4nt}{550\pi}\right)}{0.15} - \frac{X1 _{nt-1}}{50000}$

Table S1. Designed functions assessed with results presented in the Figures







Figure S1. The overall trend of designed interdependent variables (a, b, k, l) and the quantifiers in various methods (c-j), as supplementary information for Fig. 2. Note that the |*nIF*| is roughly independent from the linear 1:2:3 interdependency ratio (i, k). On the other hand, the |*IF*|, however, occasionally become dependent with this linear ratio.



Figure S2. The overall trend of designed interdependent variables (a, b, k, l) and the quantifiers in various methods (c-j), as supplementary information for Fig. 3.



Figure S3. The overall trend of designed interdependent variables (a, b, k, l) and the quantifiers in various methods (c-j), as supplementary information for Fig. 4. Note that under the large positive noise influence, the |*IF*| becomes roughly independent from the 1:2:3 ratio.



Figure S4. Assessment of methods for estimating interdependent contribution between designed 1D variables *X* and *Y*, highlighting the conditions of medium noise-contributions. The

30 figure layout is as the combination of Fig. 2 and Fig. S1: the first two columns compare the designed and estimated causal contributions, and the last two columns show the designed *dX/dt*, *dY/dt*, *X*, *Y*, and multipliers of various methods. Note the additional occurrence of opposite (negative) contributions to the common (positive) trend captured by *nIF_c* (highlighted in red boxes as compared to Fig.2). The orange arrows in f and j show inconsistent capability representing the 1:2:3 ratio especially when the signals are falsely amplified. The purple arrows indicate signals with a wrong feedback sign due to opposite causal signals to the common trend.



Figure S5. Assessment of methods for estimating interdependent contribution between designed 1D variables *X* and *Y*, under multiple conditions including opposite contribution to the common trend, time-lag between the cause and consequence, and medium noise-contributions. Same figure layout as in Fig. S4 and the coloured boxes with time-lag causality as in

40 Fig. 3. The multiple conditions follow about the same trends as in Fig. 2,3, and S4: *nIF_c* provides better estimates with opposite contribution and time-lag causality. The increased noise-contribution results in more negative contribution with positive trend (green arrows in r, as compared to Fig. 3b/j). It also limits the capability of regression in differentiating the 1:2:3 ratio and possibly lead to more false signals or even wrong feedback sign (e.g. those indicated by orange arrows in f). Estimates by *nIF_c* also suffer lower accuracy.



45 Figure S6. Assessment of methods for estimating interdependent contribution between designed 1D variables X and Y, under multiple conditions including opposite contribution to the common trend, time-lag between the cause and consequence, and large noise-contributions. Same figure layout and arrows' meanings as in Fig. S4. In addition to the conditions described in Fig. 4, there is no significant additional influence from the time-lag causality under this strong influence of noise-signals, but it may negatively affect the relatively better estimates by *IF_c* and *nIF_c* more than the already problematic estimates by regressions, as compared to Fig. 4.



Figure S7. Assessment of methods for estimating interdependent contribution between designed variables *X* and *Y* (cause-maps), at high variability frequency (~4 dX/dt sign-changes per 49 time-units) with only the north-south meridional teleconnection. The distribution of estimated causes (row 3-7) is supposed to mirror the designed effects (row 2) in the meridional direction. The estimates by *nIF_c* appear to best capture the opposite-direction causal signals, followed by *IF_c*, and the regressions are the least capable of capturing this teleconnection. However, with such high variability frequency, the errors on the temporal dimension for estimates by *IF_c* and *nIF_c* are enlarged, and accuracy of estimates by regressions are the temporal dimension.

55 regressions and m|nIF| appear more consistent on the temporal dimension.



Figure S8. Assessment of methods for estimating interdependent contribution between designed variables X and Y (cause-maps), at low variability frequency (~1 dX/dt sign-change per 49 time-units) with no teleconnection. All methods reasonably capture the interdependent contributions, but estimates by mR^2 , m|nIF|, and M_2R^2 may be better for temporal variation

60 when signals are strong (dY_{Xlat}) while estimates by *IF_c*, and *IF_c* with low interdependency (dX_{Ylat}) appear to better capture the spatial distribution, and possibly temporal variation for weak dX_{Ylat} signals.



Figure S9. Assessment of methods for estimating interdependent contribution between designed variables *X* and *Y* (cause-maps), at high variability frequency (~4-5 *dX/dt* sign-changes per 49 time-units) with no teleconnection. Under this high variability frequency, the ability to capture the interdependent contributions is limited. Errors are especially large at high latitudes with trends (feedback signs) different from low-mid latitudes where represent the major trends at a specific time. Nevertheless, the estimates by *nIF_c* appear to better capture the distribution, especially on the spatial dimensions.



Figure S10. Assessment of methods for estimating interdependent contribution between designed variables X and Y (effect-maps), at low variability frequency (~1.1 dX/dt sign change
per 49 time-units) with only the north-south meridional teleconnection. The distribution of estimated effects (row 3-6) is supposed to equal to the designed effects (row 2) in the meridional direction. Estimates by mR² appear to give the best accuracy on both temporal and spatial dimensions. There is no significant merit for other methods.



Figure S11. Assessment of methods for estimating interdependent contribution between designed variables X and Y (effect-maps), at high variability frequency (~4 *dX/dt* sign change per 49 time-units) with only the north-south meridional teleconnection. The distribution of estimated effects (row 3-6) is supposed to equal to the designed effects (row 2) in the meridional direction. Estimates by *mR*² appear to give the best accuracy on both temporal and spatial dimensions. Although the estimates by *m|nIF|* may better capture few weak signals, it appears to introduce more errors with overestimated weak signals. For the temporal dimension, the estimates by *mR*² and *m|nIF|* could be more reliable especially at high-frequency variability.



Figure S12. Assessment of methods for estimating interdependent contribution between designed variables *X* and *Y* (effect-maps), at low variability frequency (~1 dX/dt sign-change per 49 time-units) with no teleconnection. Estimates by mR^2 and m|nIF| appear to give more consistent accuracy on both temporal and spatial dimensions when the signals are weak $(dX_{Y_x}$ i.e. when the noise is strong), but that advantage may be less obvious when signals are strong (dY_x) .



Figure S13. Assessment of methods for estimating interdependent contribution between designed variables *X* and *Y* (effect-maps), at high variability frequency (~4-5 *dX/dt* sign-change per 49 time-units) with no teleconnection. Estimates by *mR*² appear to give the best accuracy on both temporal and spatial dimensions. There is no significant merit for other methods.