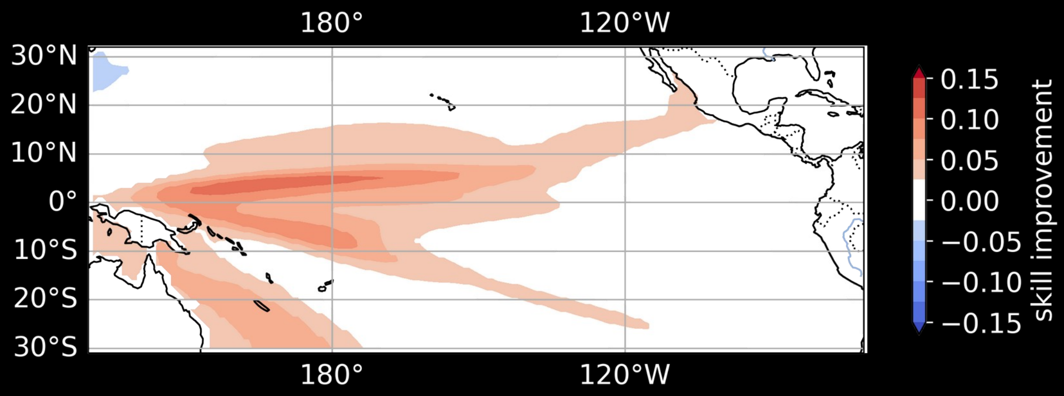
Characterizing Nonlinearities in CESM2 ENSO Dynamics using Machine Learning Technique



Jakob Schlör, Antonietta Capotondi, Matthew Newman, Bedartha Goswami

NOAA-PSL Boulder & Universität Tübingen

ENSO Forecast: Statistical (data-driven) models

- **Linear Inverse Model (LIM)**
  - Penland & Matrosova (1994)
  - LIM skill is comparable to NMME (Newman and Sardeshmukh, 2017)

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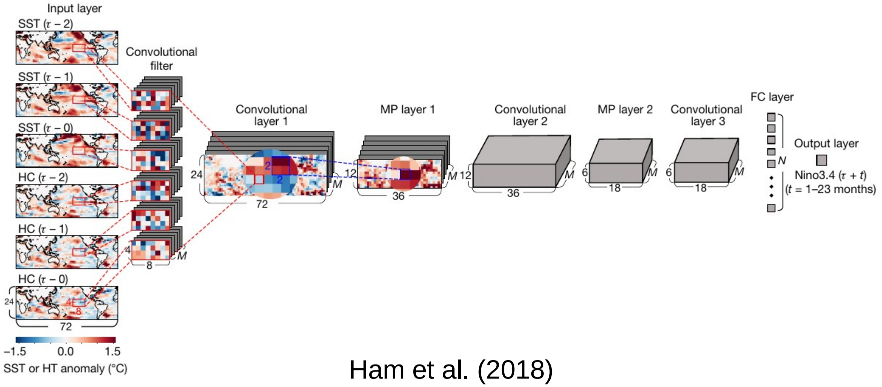

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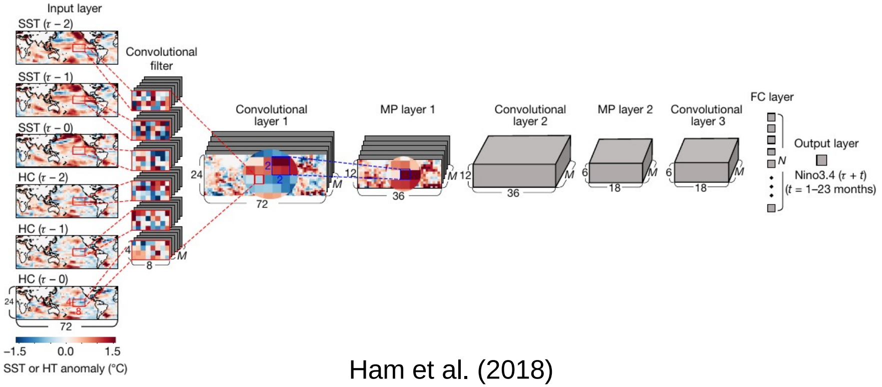

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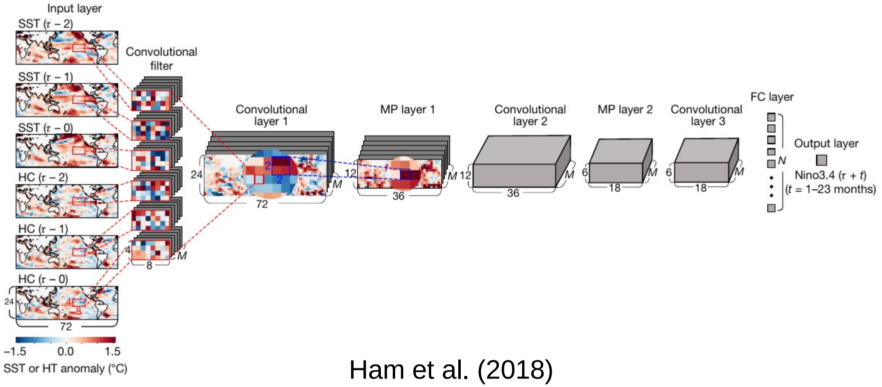

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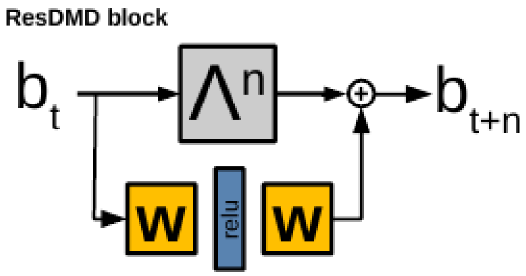
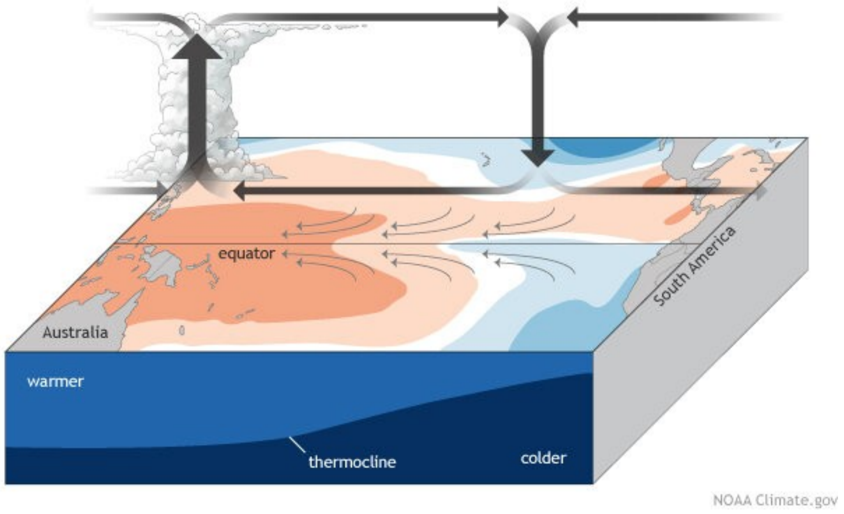


Rodrigues et al. (2021)

ENSO Dynamics

$$\frac{dx}{dt} = \underbrace{F\left(x\left(t\right)\right)}_{\text{deterministic}} + \underbrace{G\left(x\left(t\right)\right)\xi}_{\text{stochastic}}$$



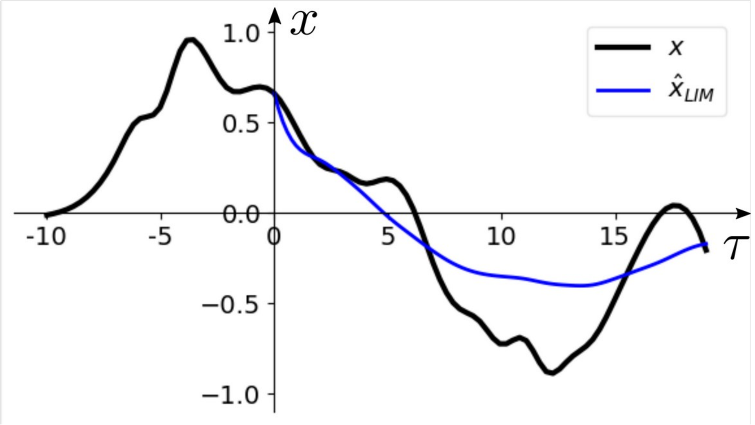
- Slow varying deterministic ocean dynamics
- Ocean is stochastically forced by atmosphere

Penland & Ewald, Phil. Trans. R. Soc. (2008)

Linear Inverse Model (LIM)

$$\frac{dx}{dt} = \underbrace{F\left(x\left(t\right)\right)}_{\text{deterministic}} + \underbrace{G\left(x\left(t\right)\right)\xi}_{\text{stochastic}}$$

$$\approx L\,x + \xi$$



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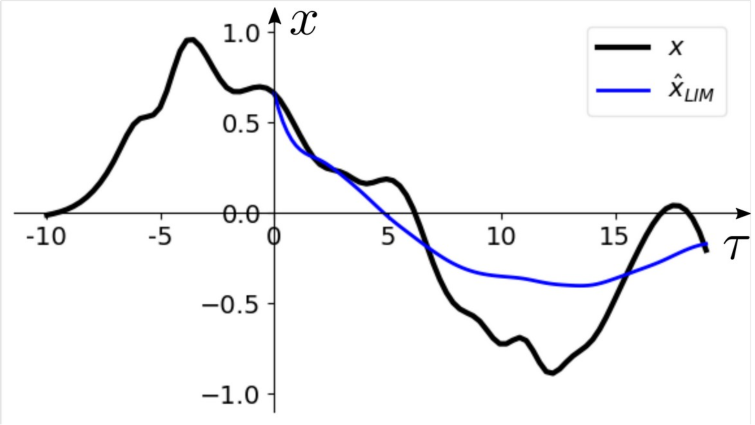
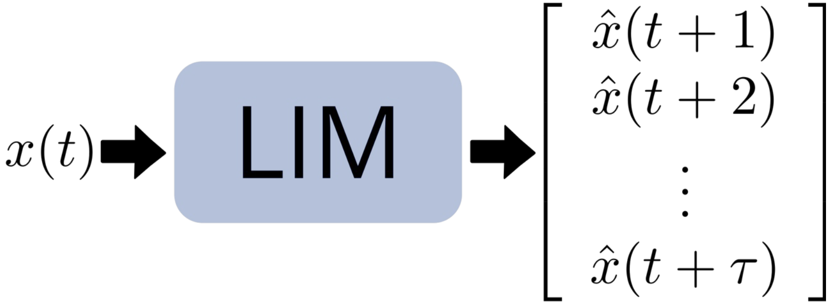


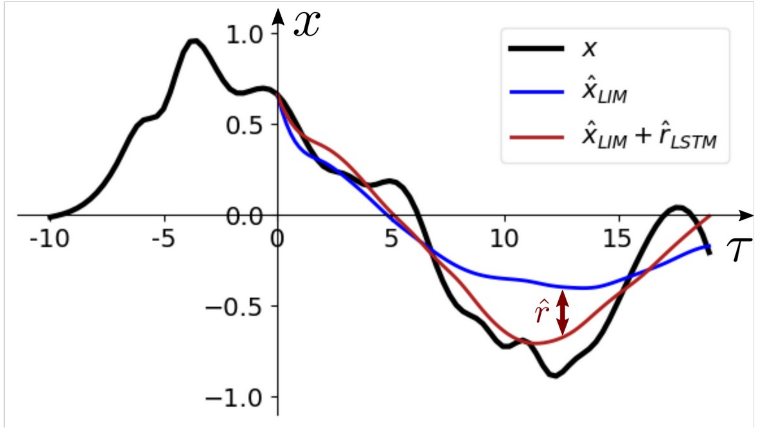


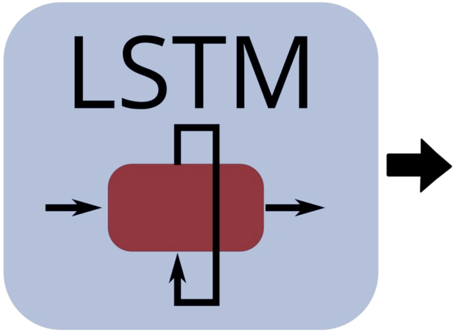
Penland & Matrosova (1994)

Long Short Term Memory (LSTM) Network

$$\frac{dx}{dt} = \underbrace{F\big(x(t)\big)}_{\text{deterministic}} + \underbrace{G\big(x(t)\big)\xi}_{\text{stochastic}}$$

$$\approx L\,x + \underbrace{N(x)}_{} + \xi$$





$$\begin{bmatrix} \hat{x}(t+1) + \hat{r}(t+1) \\ \hat{x}(t+2) + \hat{r}(t+2) \\ \vdots \\ \hat{x}(t+\tau) + \hat{r}(t+\tau) \end{bmatrix}$$

Hochreiter & Schmidthuber (1997)

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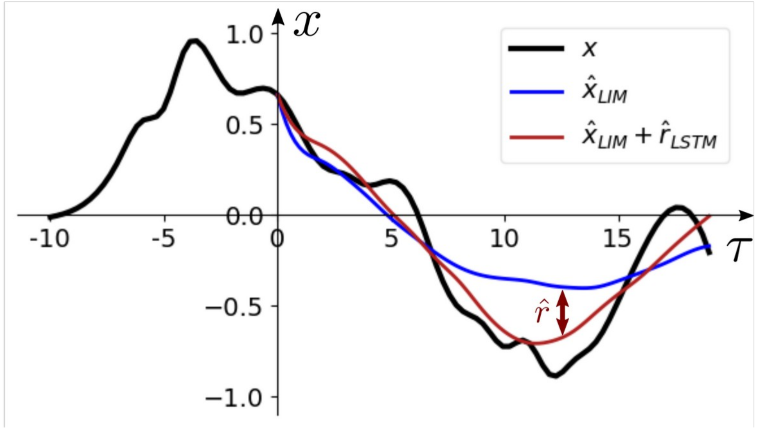

- LSTM is a Recurrent Neural Networks
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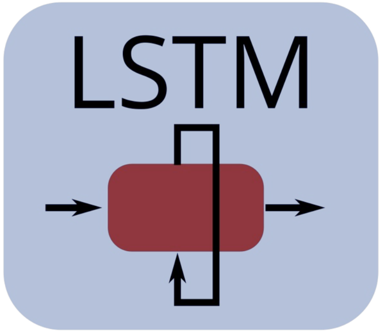
- Captures nonlinear and non-markovian dynamics



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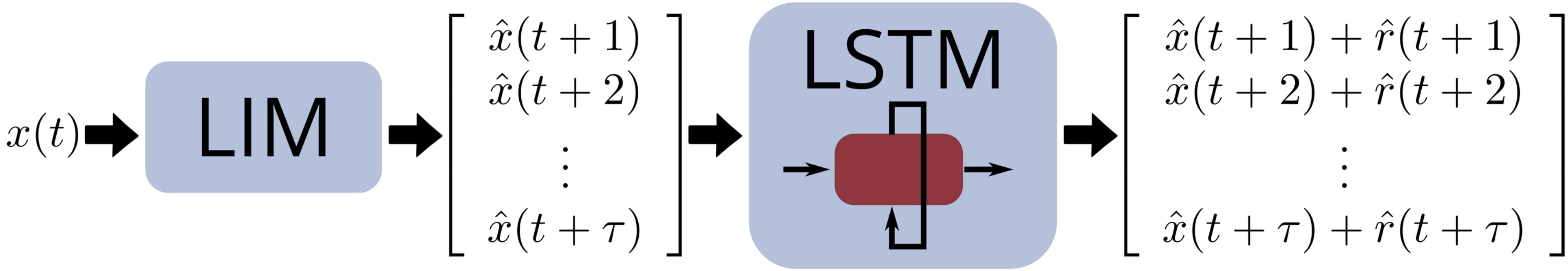
LIM + LSTM



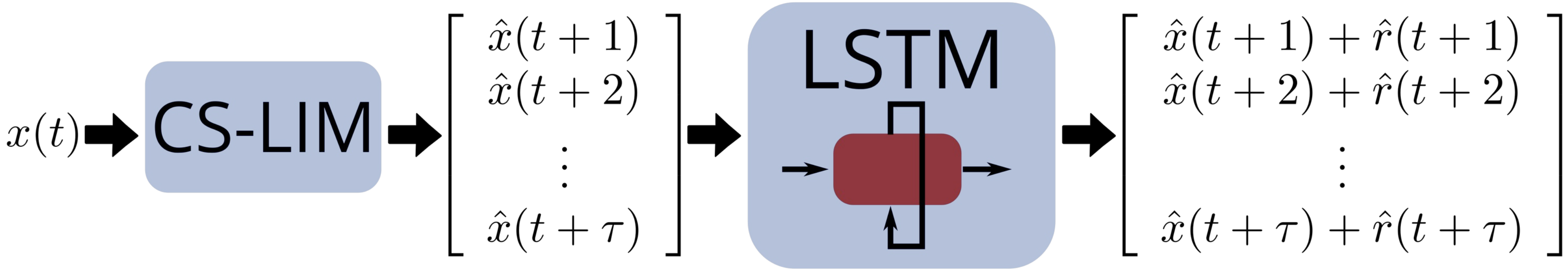
- Training using mean-square error loss:

$$\mathscr{L}\left(x,\hat{x}+\hat{r}\right)=\frac{1}{N}\sum\left(x-\left(\hat{x}+\hat{r}\right)\right)^2$$

Characterizing Nonlinearities in ENSO Dynamics

Jakob Schlör

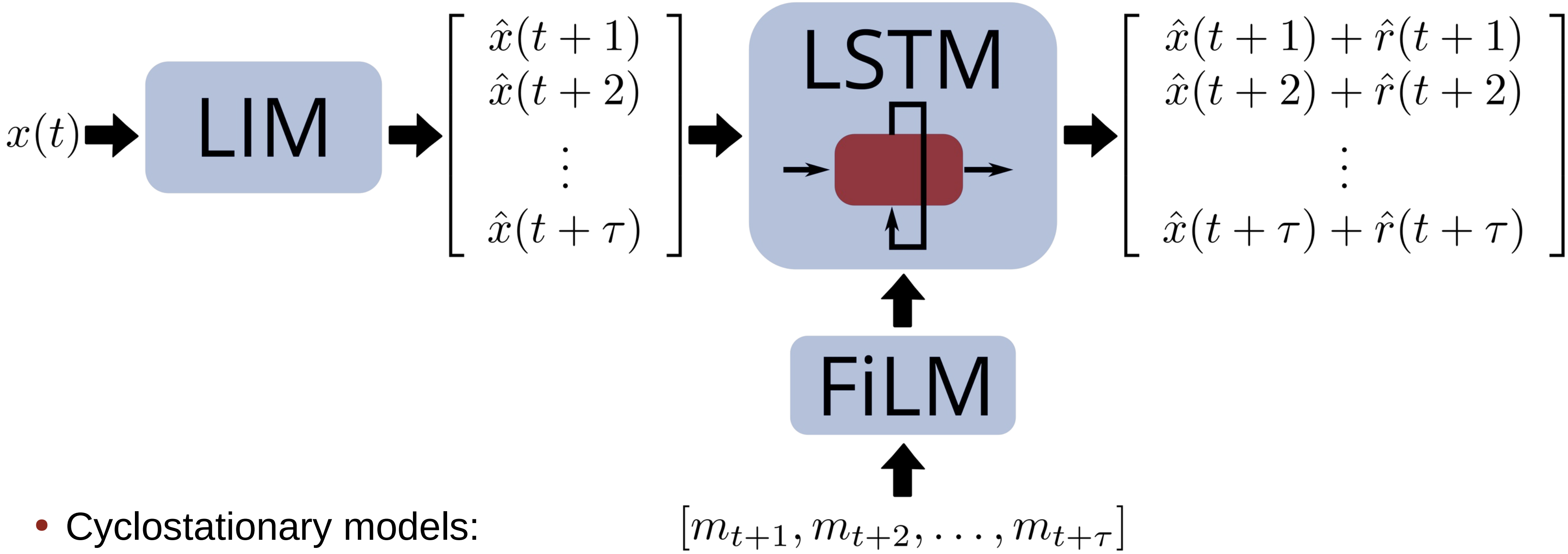
LIM + LSTM



- Cyclostationary models:
  - CS-LIM

Shin et al., JoC (2021)
E. Perez et al., AAAI (2018)

LIM + LSTM

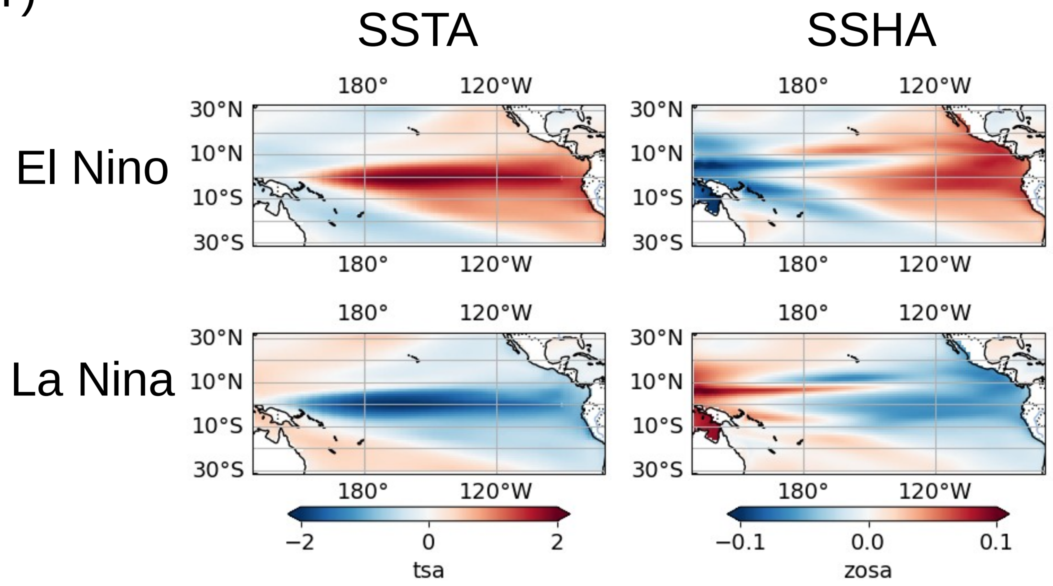


- Cyclostationary models:
  - CS-LIM
  - CS-LSTM: Conditioning on season using Feature-wise Linear Modulation (FiLM)

E. Perez et al., AAAI (2018)

Data: CESM2 Preindustrial Control

- Monthly sea surface temperature (SST) and sea surface height (SSH)
- Tropical Pacific (30°S-30°N, 130°E-70°W)
- Remove monthly mean



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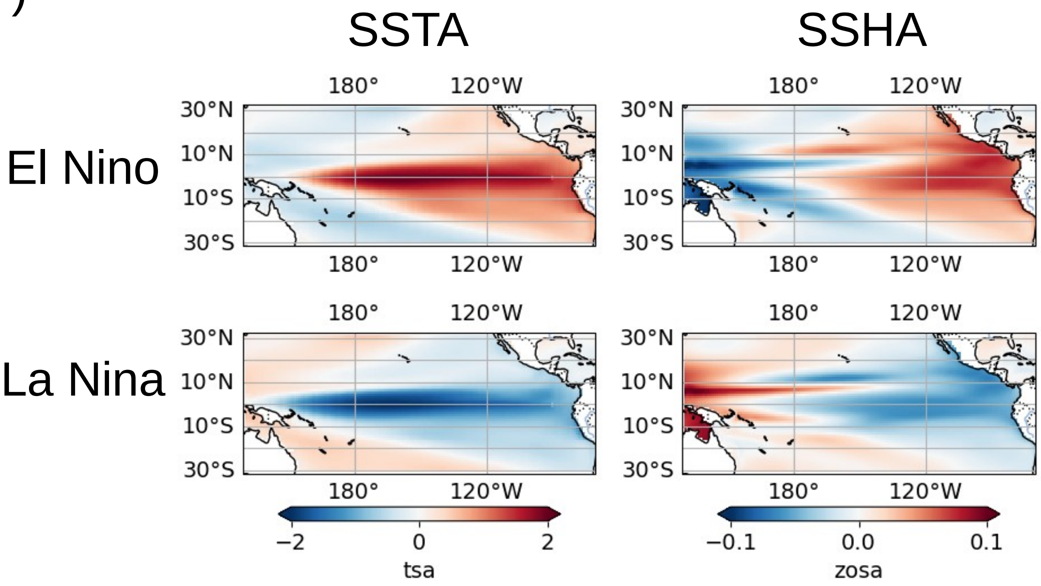

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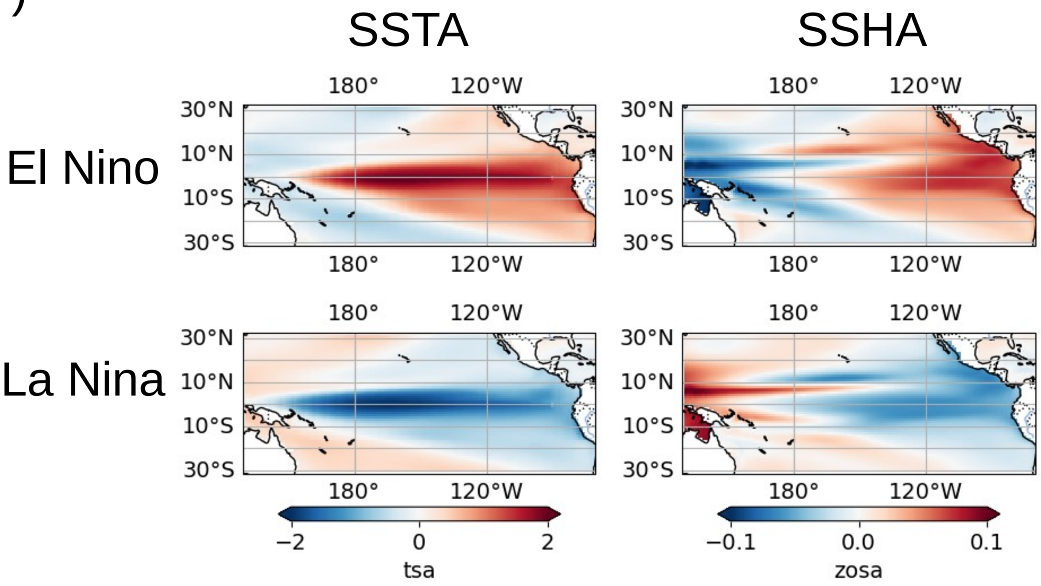
- First 20 PCs of SSTA and 10 PCs of SSHA



Evaluation Metrics

- Evaluation in grid space
- Skill score:

$$\epsilon = 1 - RMSE(\hat{x}, x) / \sigma$$

x : data
$\hat{x}$: prediction
σ : standard deviation of x

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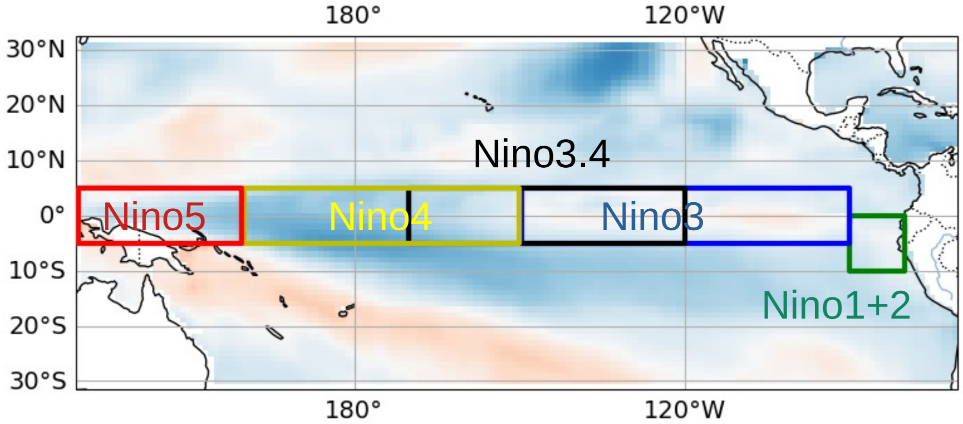
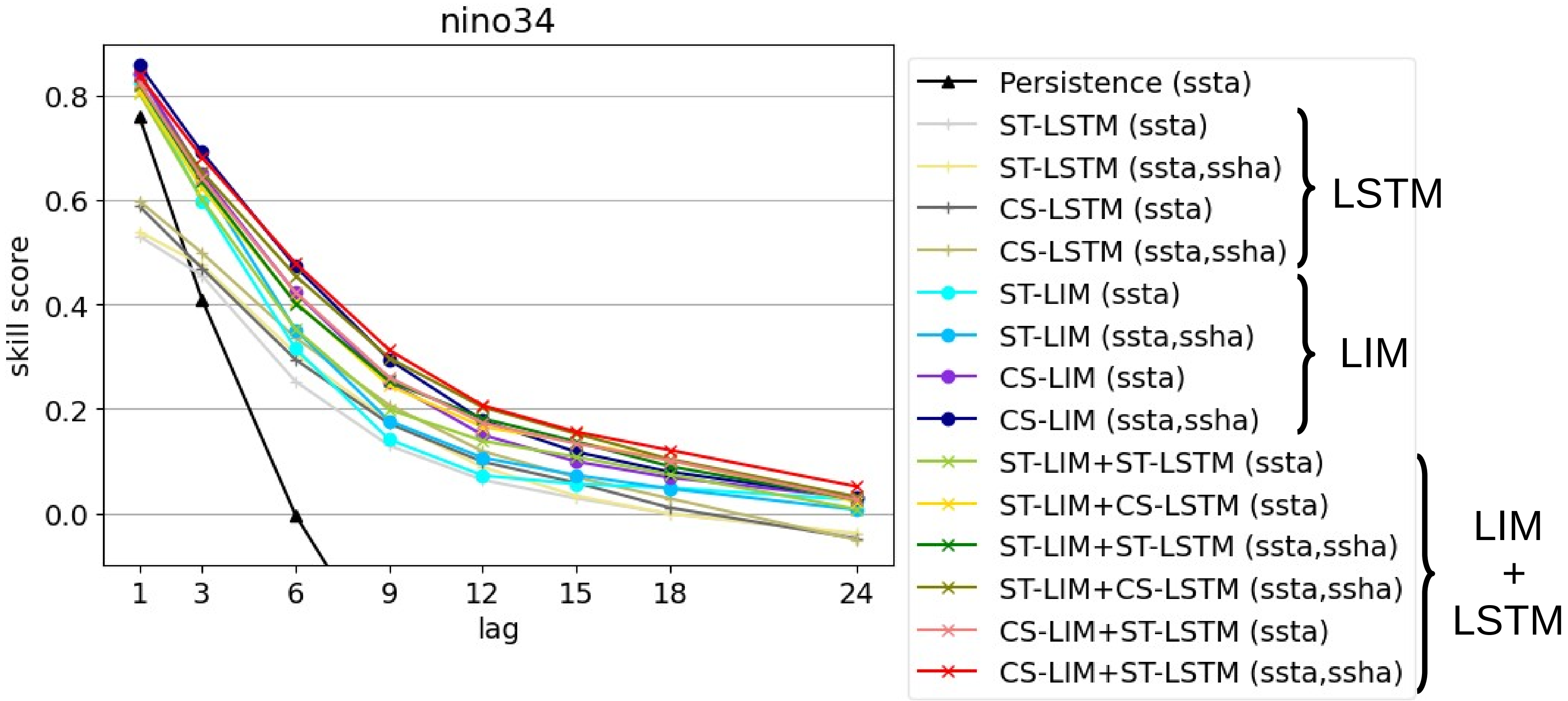
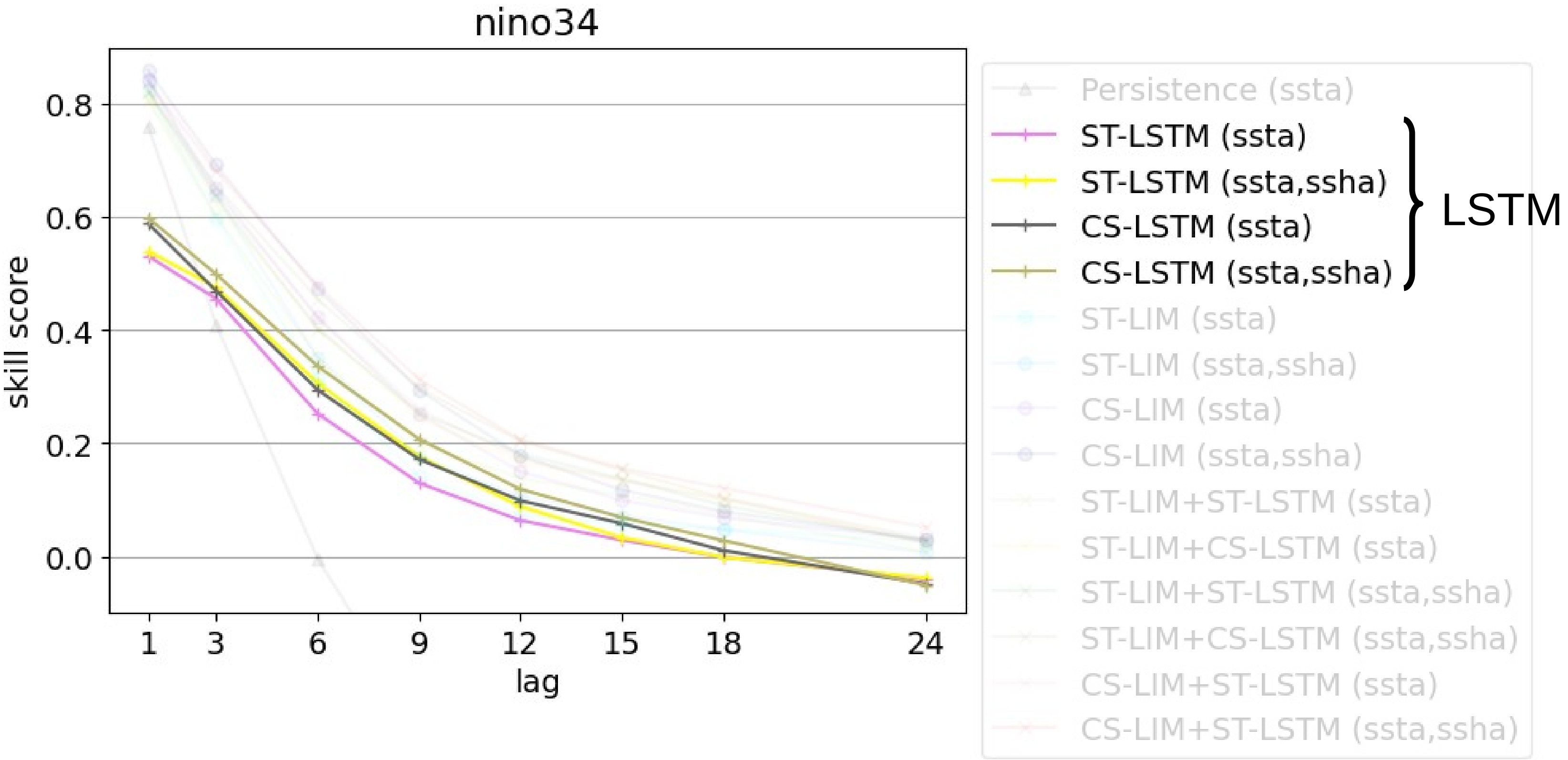
- Averages over Niño-regions



Results: Zoo of experiments



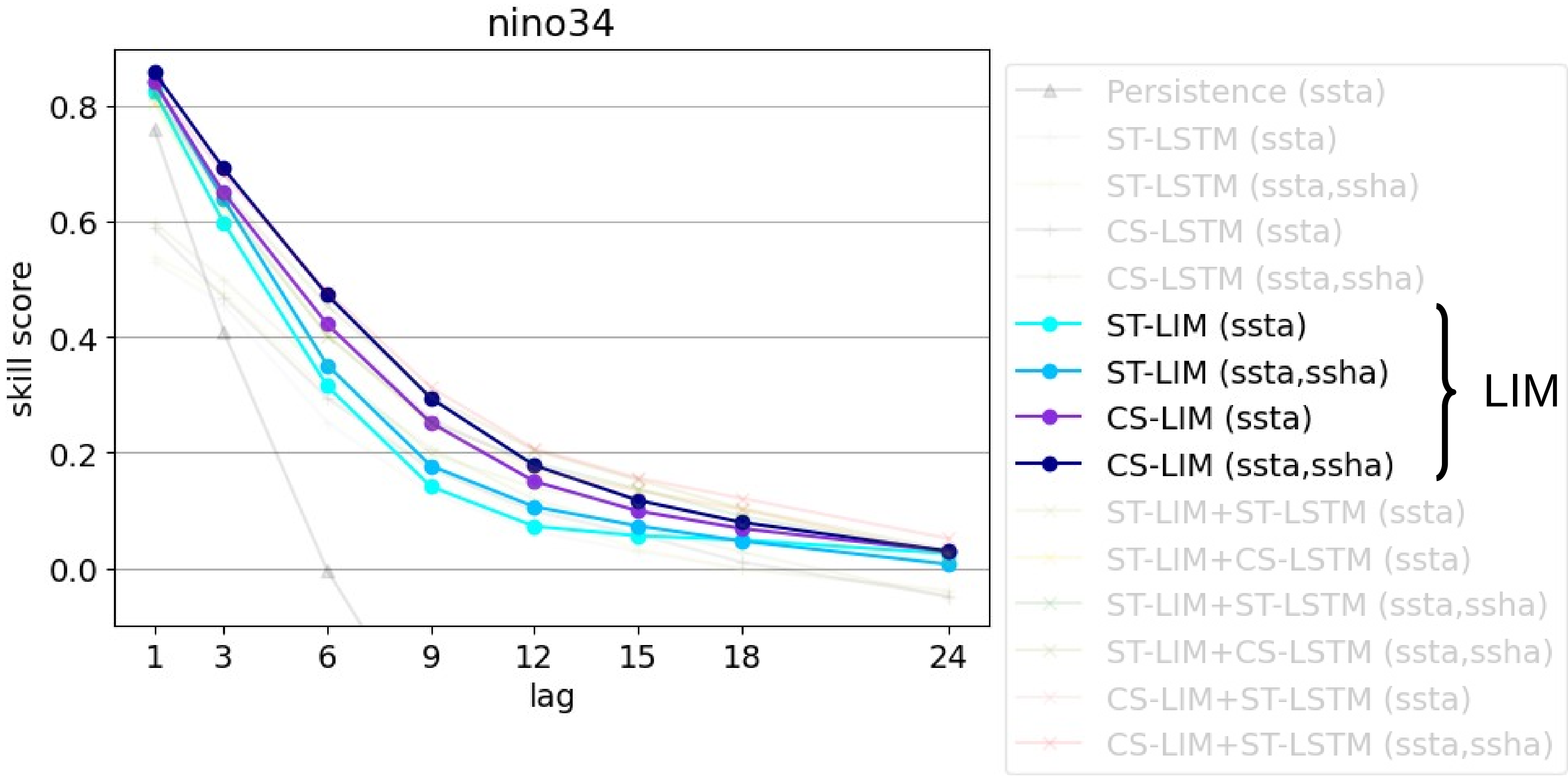
Pure LSTM



Learning the whole dynamics is harder than only residuals

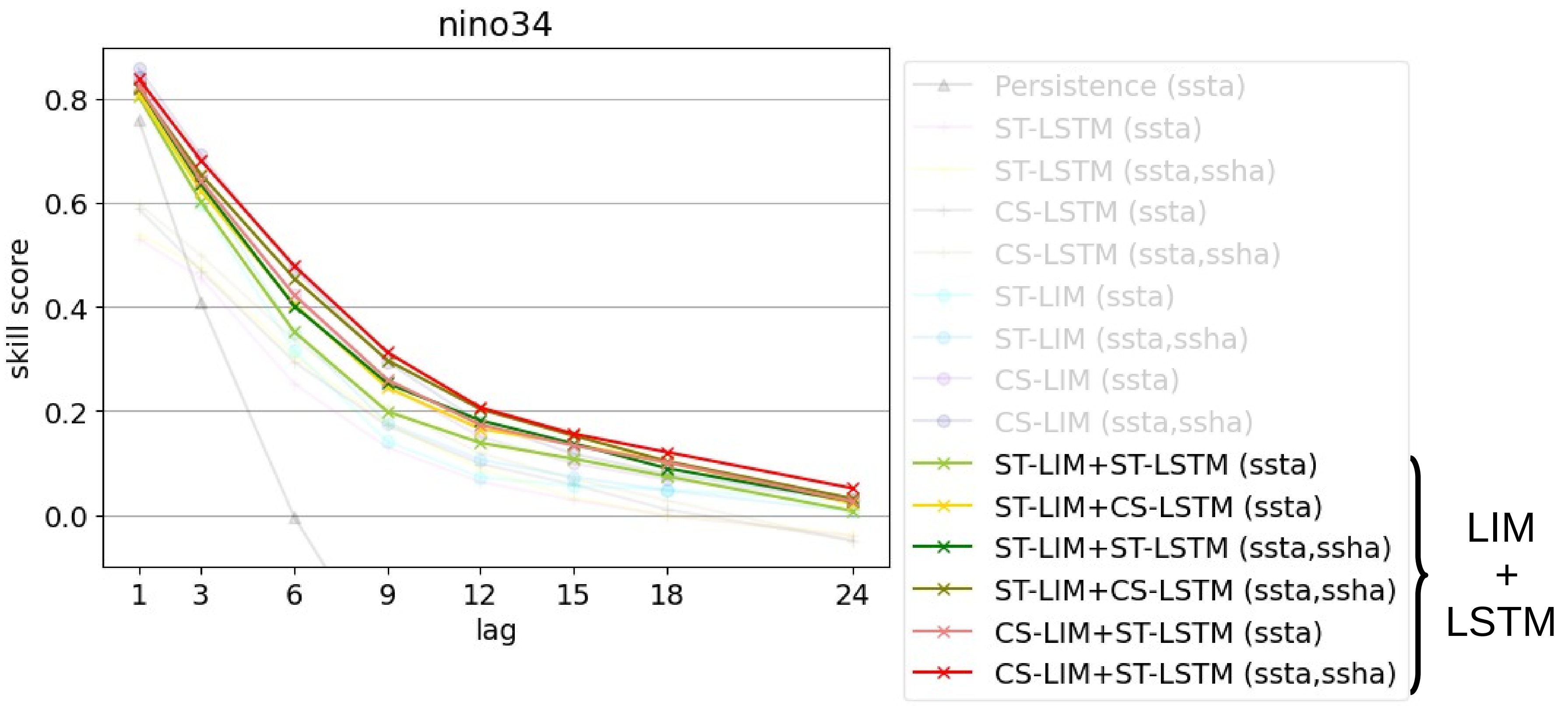
- More data?

LIMs



- LIM prediction improves by including seasonality & ocean variable

LIM + LSTM



nino34
skill score
lag
0.8
0.6
0.4
0.2
0.0
1
3
6
9
12
15
18
24
Persistence (ssta)
ST-LSTM (ssta)
ST-LSTM (ssta,ssha)
CS-LSTM (ssta)
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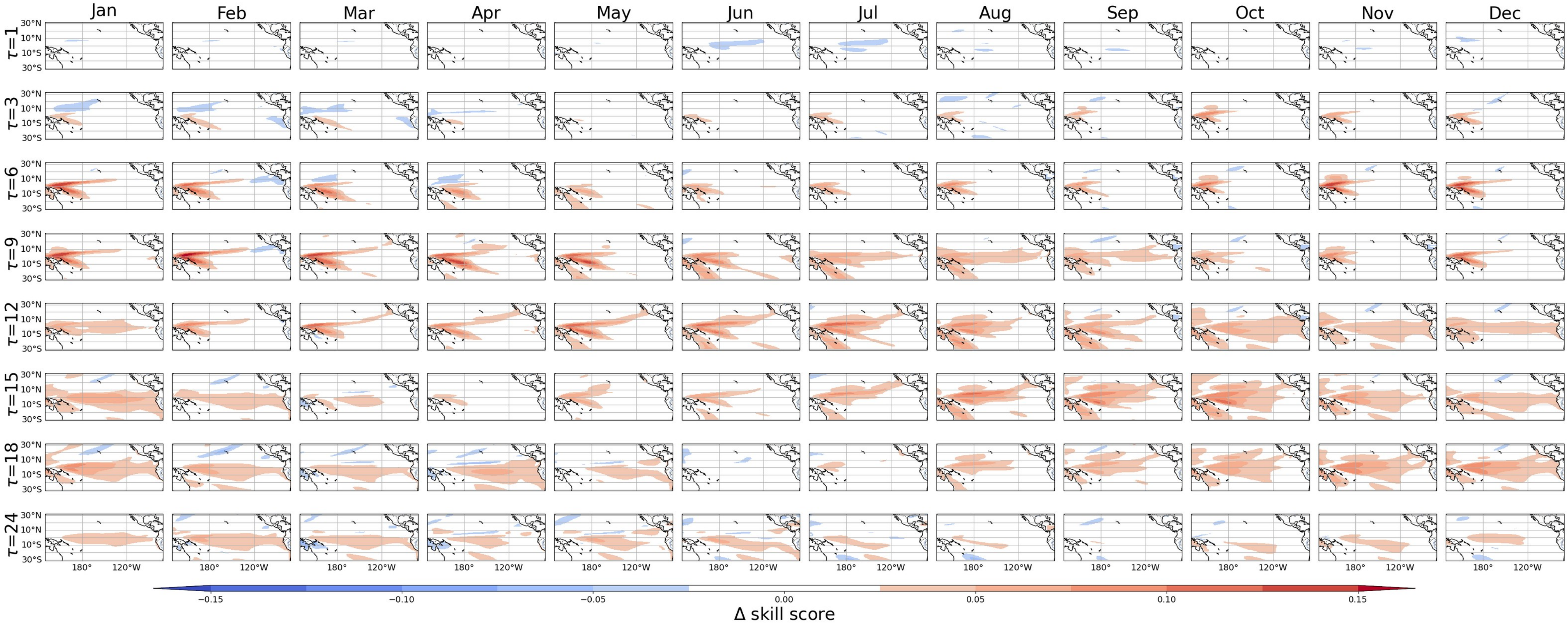
LIM
+
LSTM

What dynamics does the LSTM pick up?



Skill improvement by LSTM, i.e. [CS-LIM+LSTM] - CS-LIM

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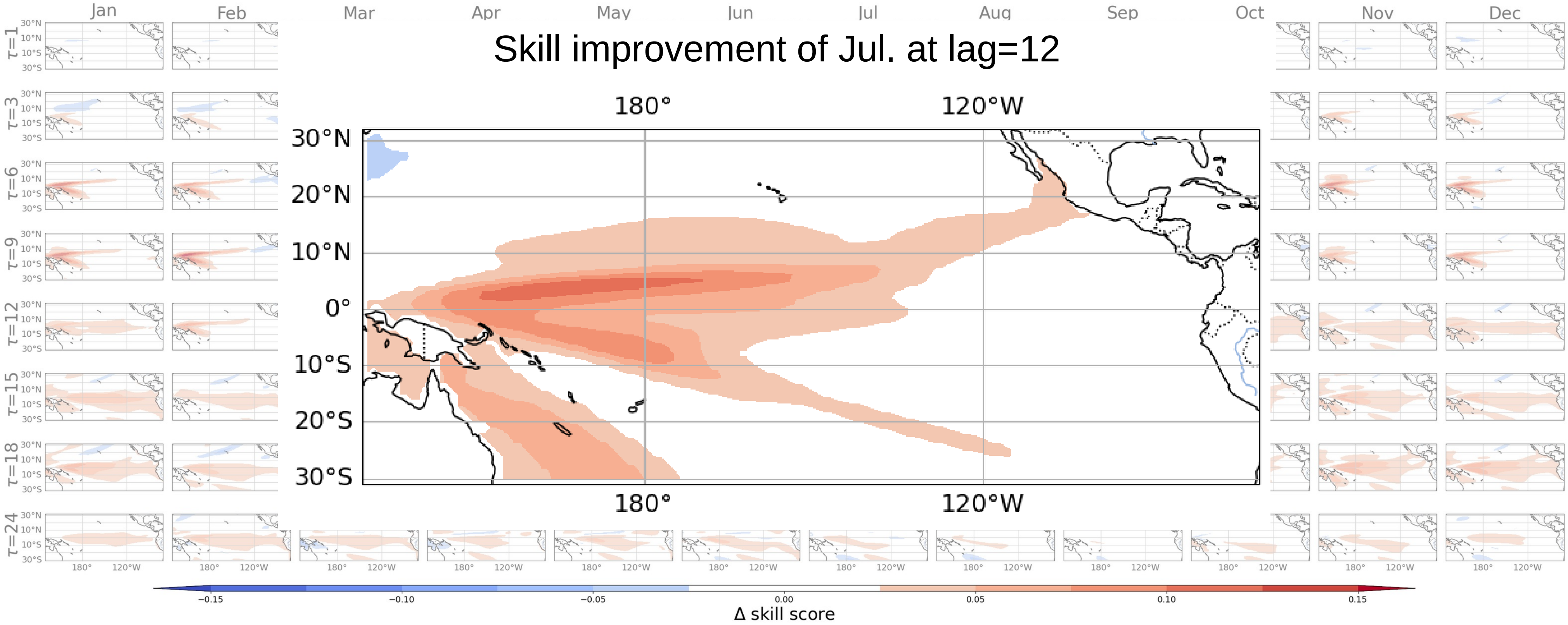

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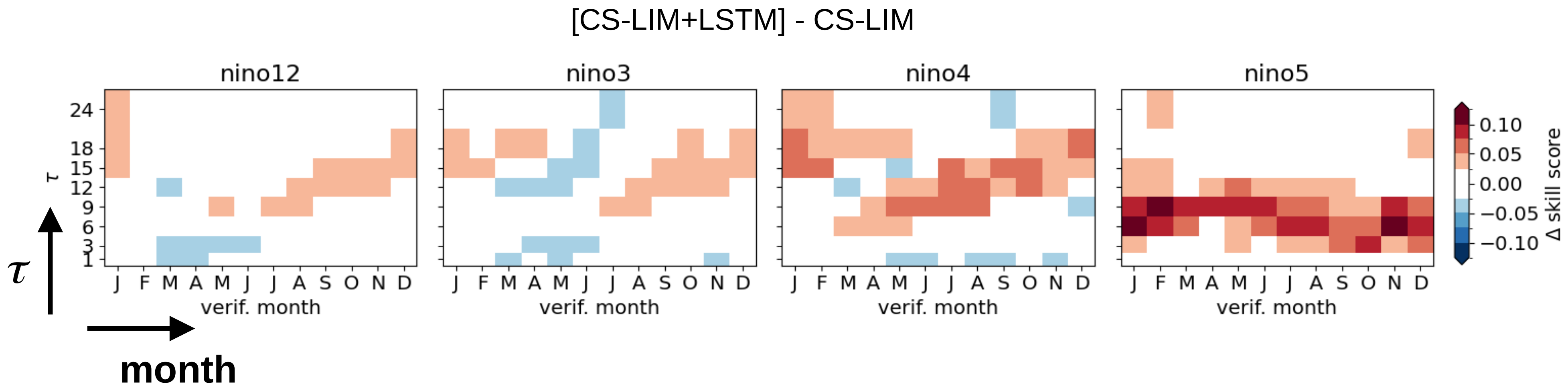

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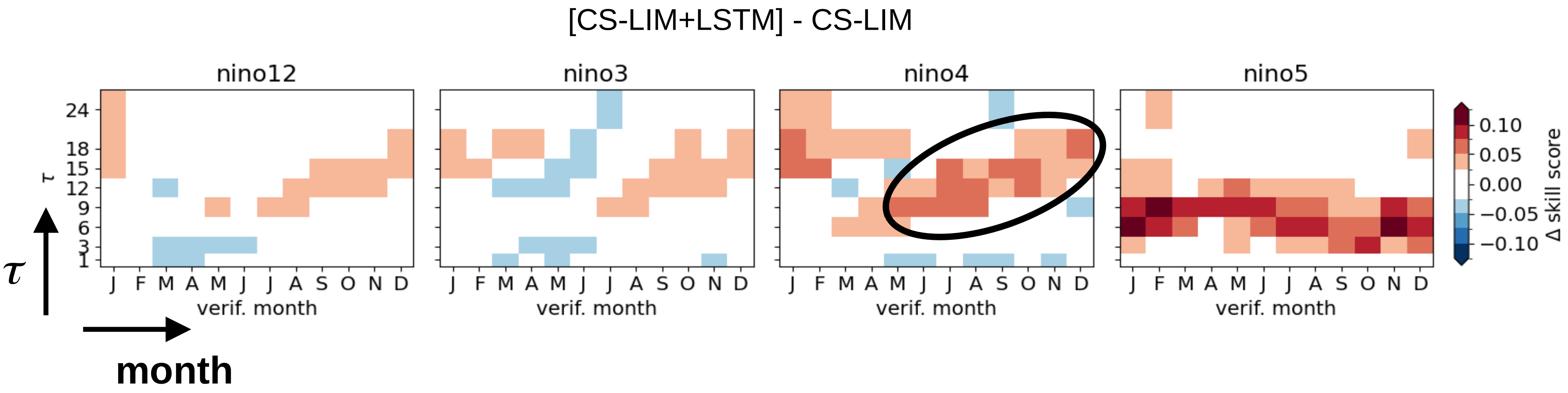

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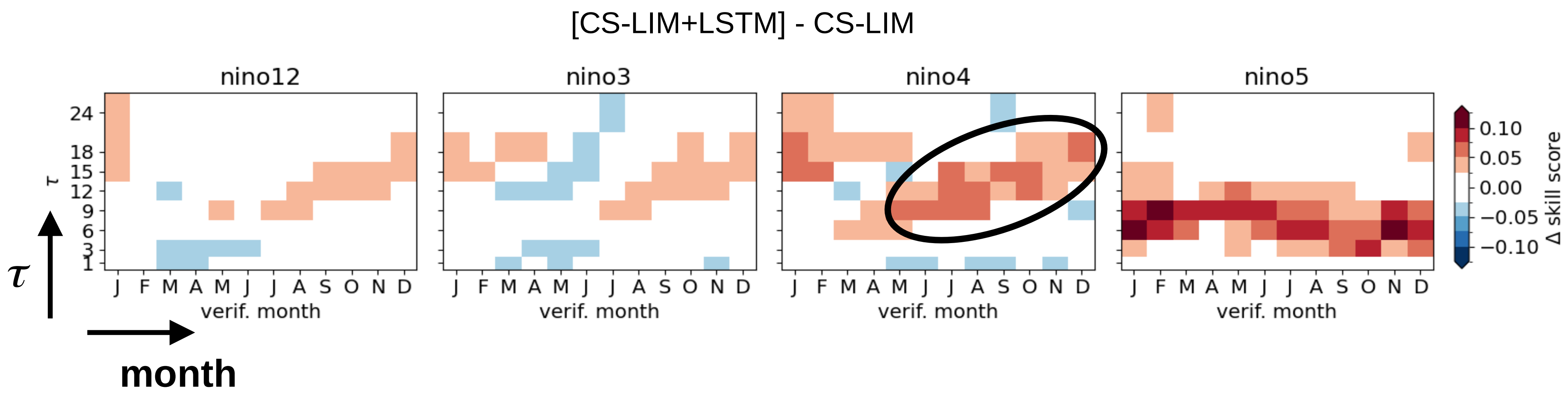
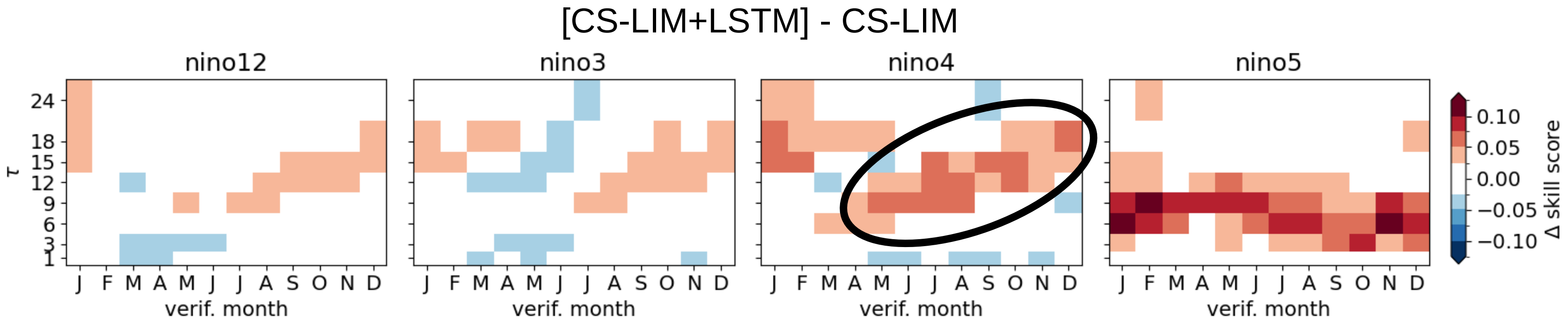


- LSTM improves forecast from 9-18 months in the Western Pacific
- Improved forecasts are initialized in July – December
- We know it is NOT:
  - Seasonal cycle (linear)
  - Ocean memory

Hypothesis: El Niño - La Niña asymmetry

All



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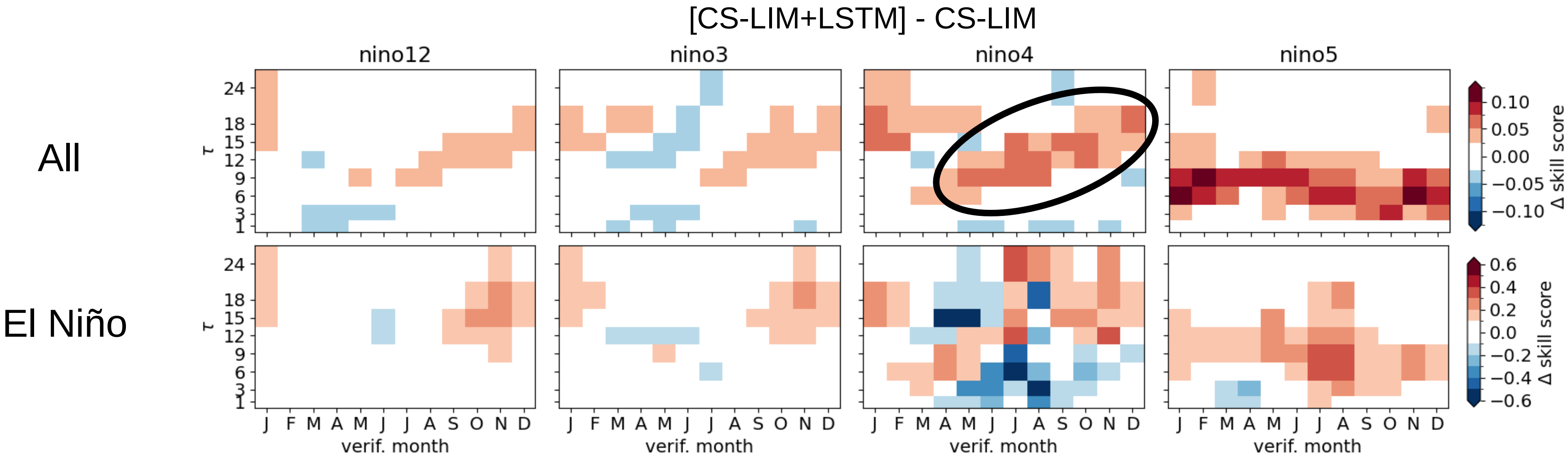

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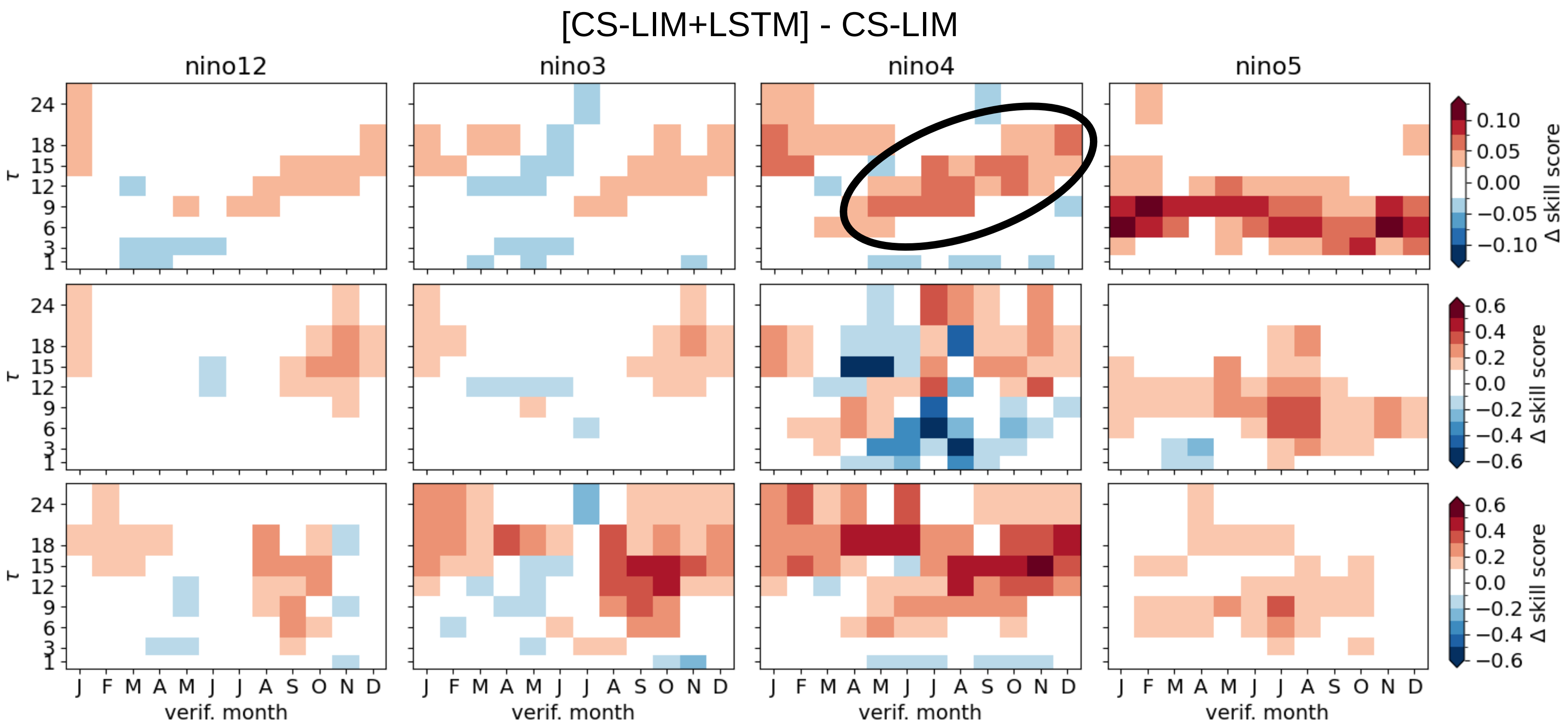

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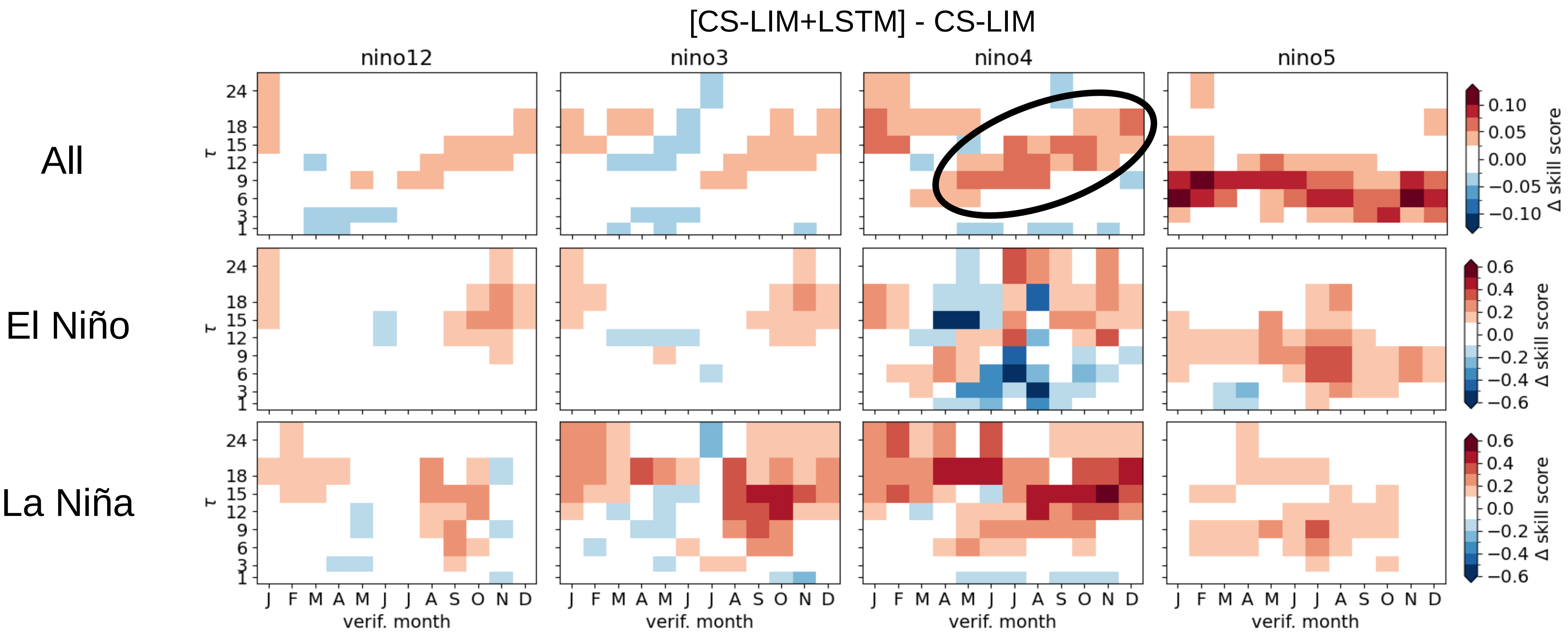

Skill improvement by LSTM can be partially explained by ENSO asymmetry.

Conclusion

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Outlook

- Disentangle nonlinearities from markovianity by idealized experiments
- Apply on observational data

Thank you!

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Matthew Newmann

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machineclimate.de
@schloer_jakob
jakob.schloer@uni-tuebingen.de

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Appendix

Linear Inverse Models

$$\boxed{\frac{dx}{dt} = Lx + \xi}$$

τ : lag time
ξ : white noise forcing
$C(0)$: data covariance
$C(\tau)$: lagged covariance

Stationary LIM:

$$\hat{x}(t+\tau) \sim N\left(\mathbf{exp}\left(\boldsymbol{L}^{ST}\boldsymbol{\tau}\right)\boldsymbol{x}(\boldsymbol{t}), \Sigma^{ST}\right)$$

with same linear operator for all times: $L^{ST} = \tau^{-1}\ln\left[C(\tau)C(0)^{-1}\right]$

Cyclostationary LIM:

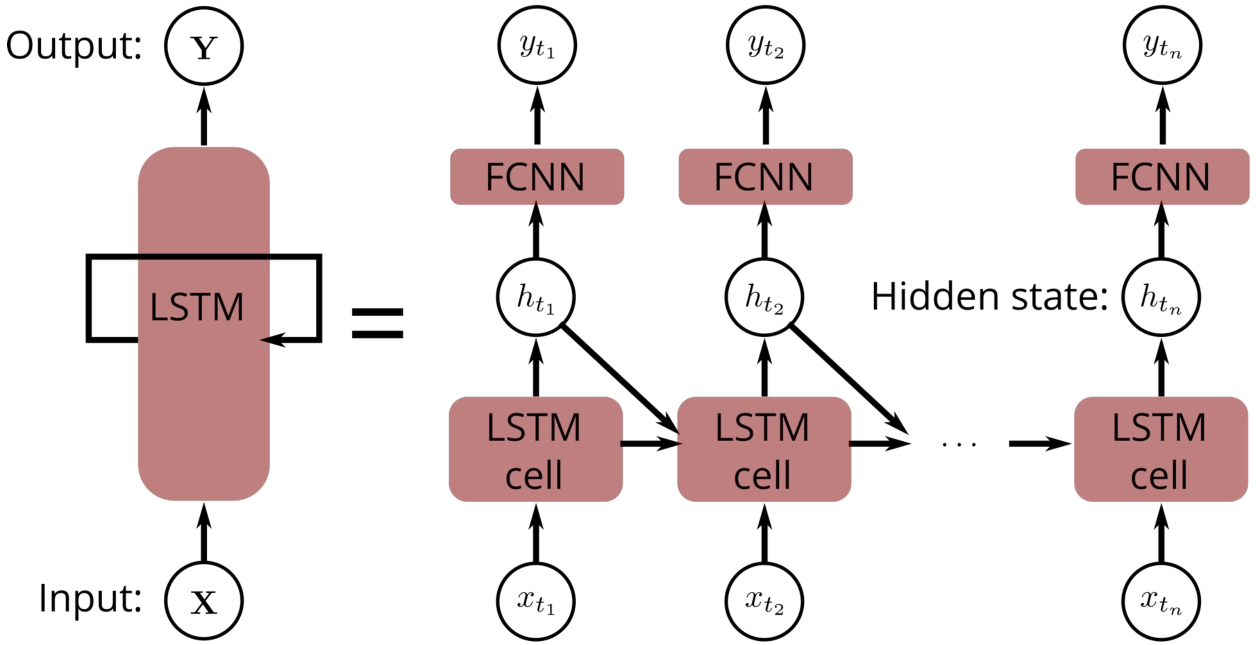
$$\hat{x}_j(t+\tau) \sim N\left(\mathbf{exp}\left(\Sigma_{n=0}^{\tau-1}\boldsymbol{L}_{j-n}^{CS}\right)\boldsymbol{x}_{j-\tau}(\boldsymbol{t}), \Sigma_{j-\tau\rightarrow j}^{CS}\right)$$

with linear operator for each month $j = 1, \ldots, 12$: $L_j^{CS} = \tau_0^{-1}\ln\left[C_j(1)C_j(0)^{-1}\right]$

example Jan $\rightarrow$ Mar: $\hat{x}_3(t+2) \sim N\left(\mathbf{exp}\left(\boldsymbol{L}_{2\rightarrow3}^{CS} + \boldsymbol{L}_{1\rightarrow2}^{CS}\right)\boldsymbol{x}_1(\boldsymbol{t}), \Sigma_{1\rightarrow3}^{CS}\right)$

Shin et al., JoC (2021)

Long Short Term Memory (LSTM) Network



- LSTM is a special kind of Recurrent Neural Networks
- Basic idea: Different time-scales (memory) should be captured by different variables
- Captures nonlinear and non-markovian dynamics

Hochreiter & Schmidthuber (1997)

Long Short Term Memory (LSTM) Network

Cell state: $C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$

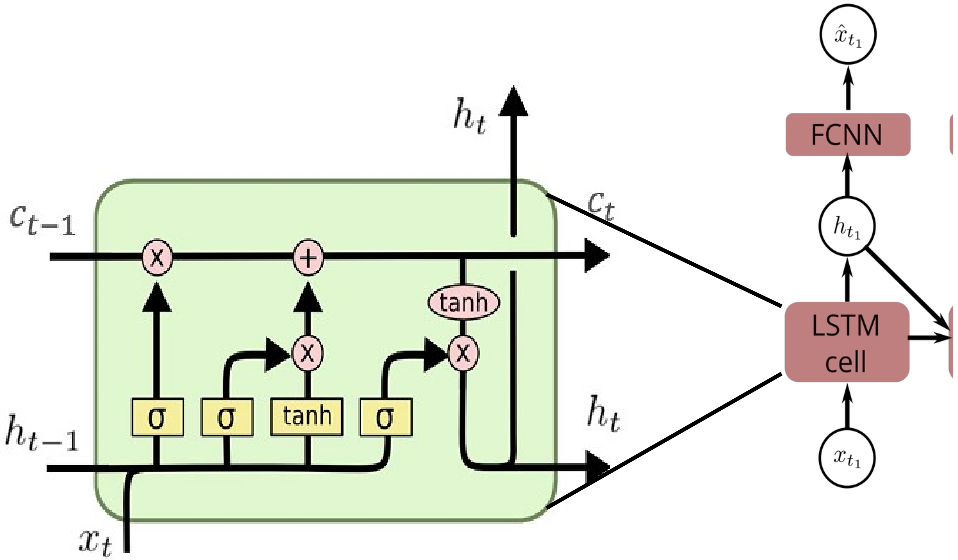
Forget gate: $f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] \; + \; b_f\right)$

Input gate: $i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] \; + \; b_i\right)$

$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] \; + \; b_C)$

Hidden state: $o_t = \sigma\left(W_o \; [h_{t-1}, x_t] \; + \; b_o\right)$

$h_t = o_t * \tanh\left(C_t\right)$



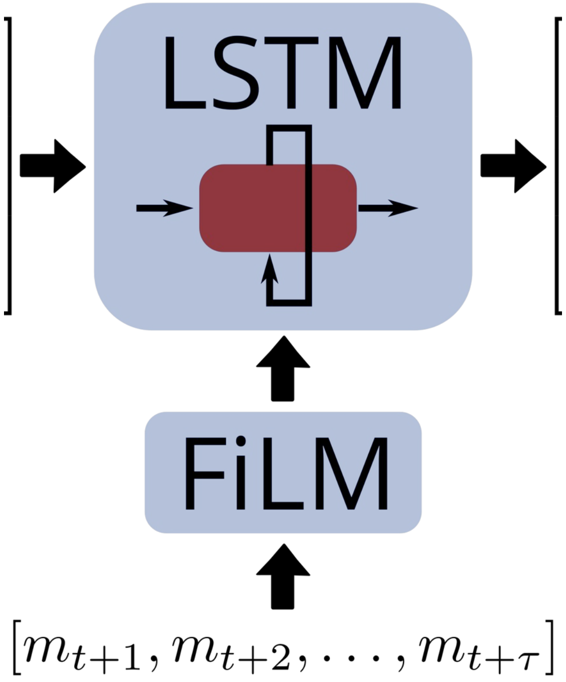
Hochreiter & Schmidthuber (1997)
https://colah.github.io/posts/2015-08-Understanding-LSTMs/

Feature-wise Linear Modulation (FiLM)

- FiLM is used for conditioning NN on external input
- Feature-wise affine transformation of input,
  i.e. scaling and shifting applied element-wise

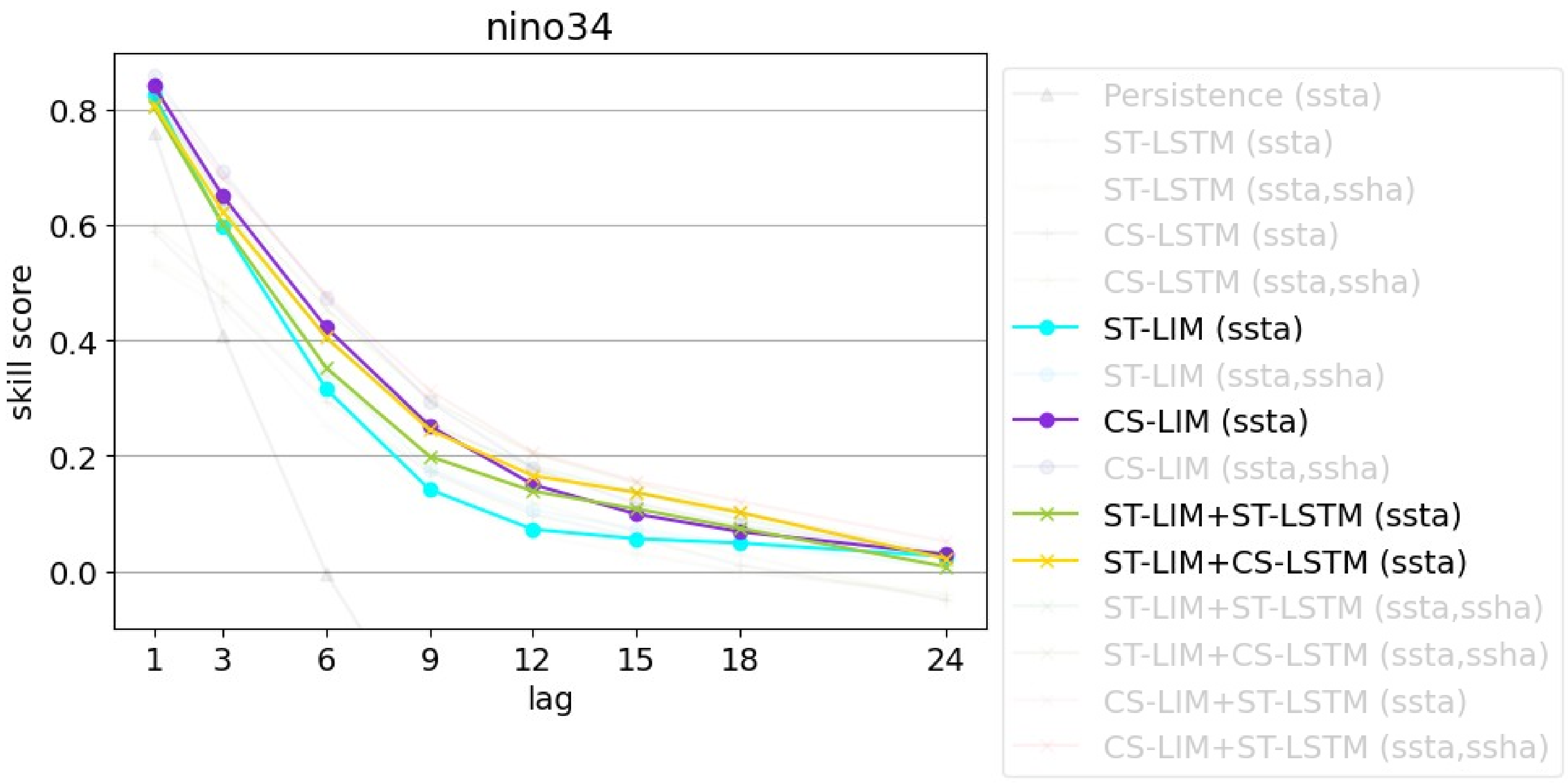
$$\mathrm{FiLM}(x) = \gamma(z) * x + \beta(z)$$

$$\begin{aligned} z &: \text{conditional input} \\ \gamma(z) &: \text{scaling network} \\ \beta(z) &: \text{bias network} \end{aligned}$$



https://distill.pub/2018/feature-wise-transformations/
Perez et al., FiLM(2017)

The Seasonal Cycle



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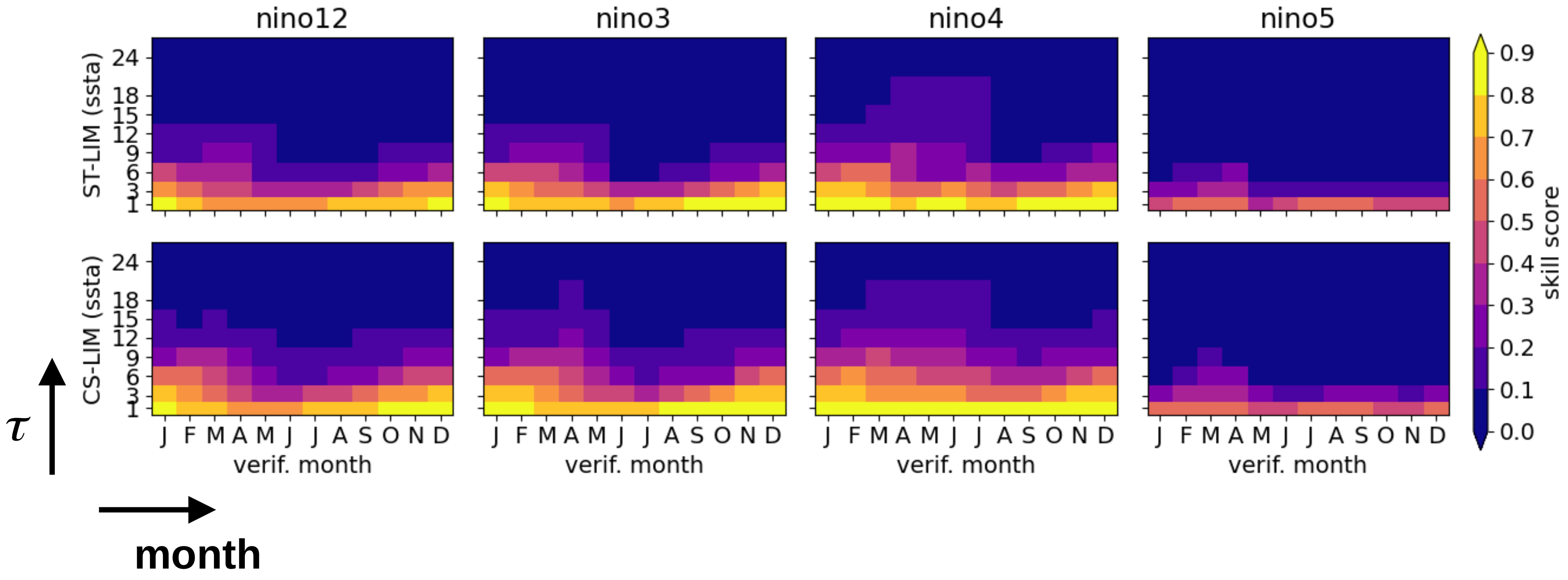

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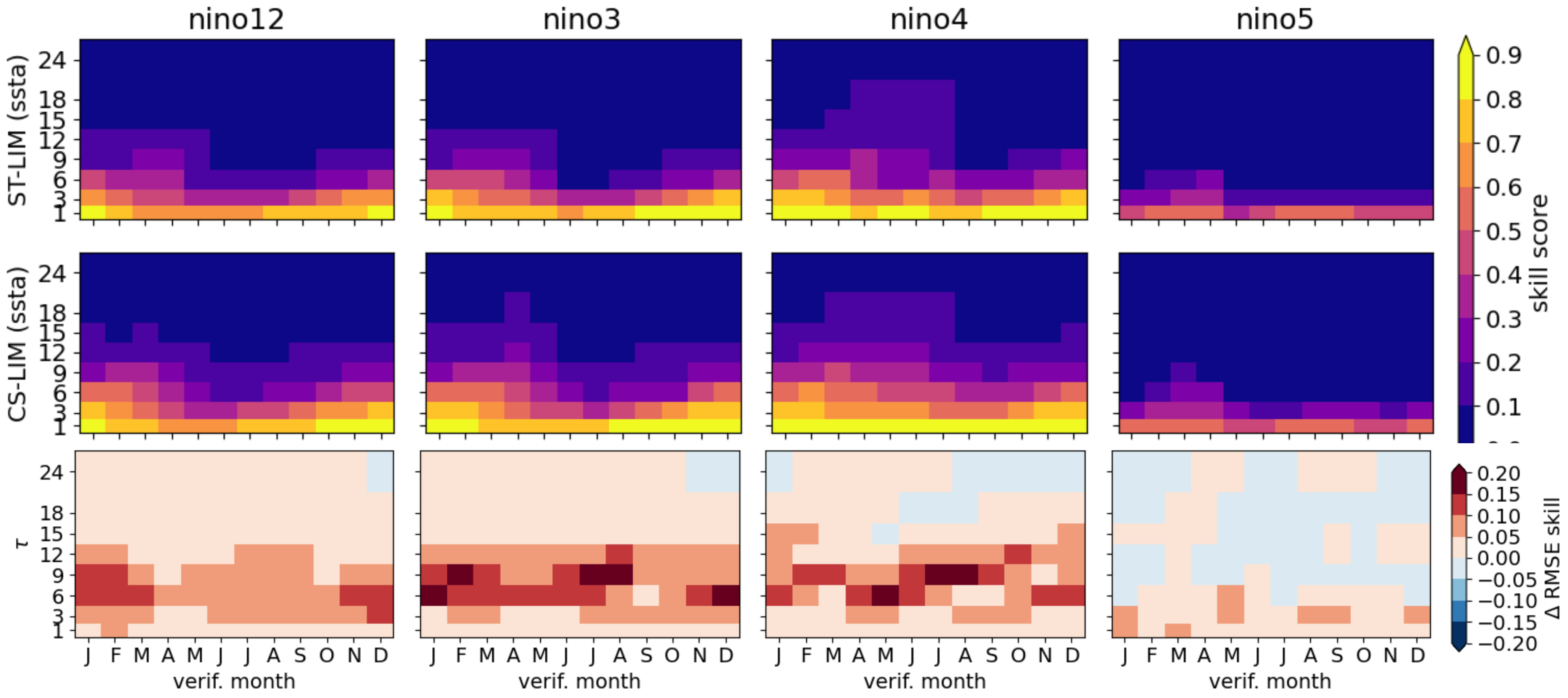
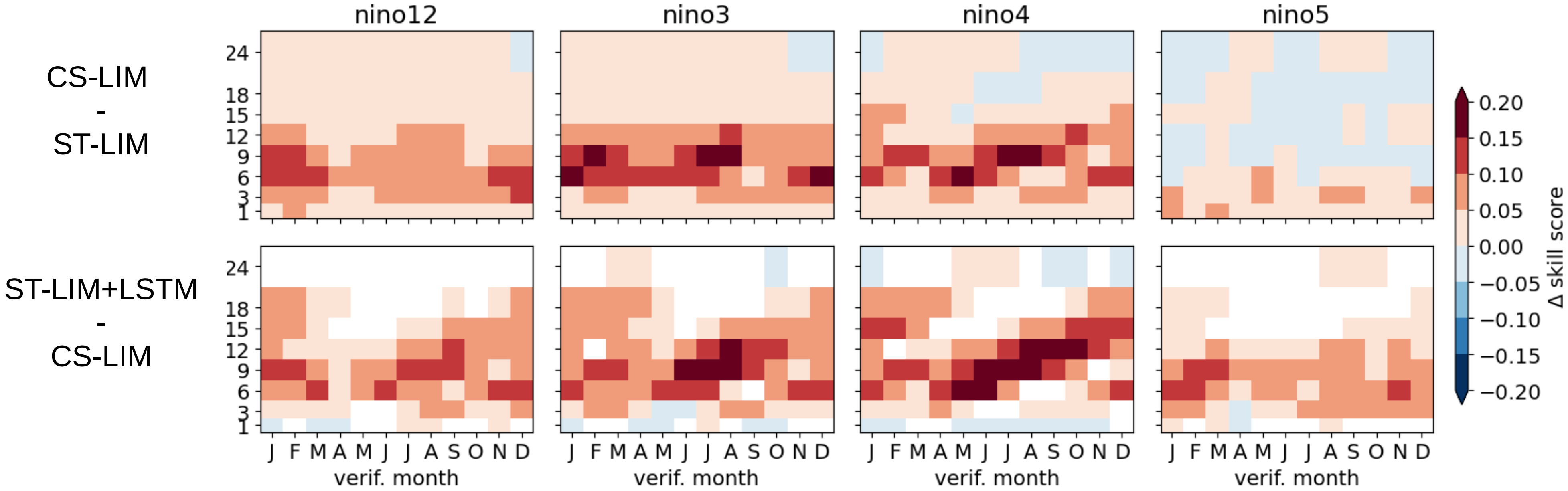


CS-LIM
-
ST-LIM

- Including seasonality (linearly) improves forecast between 3-9 month

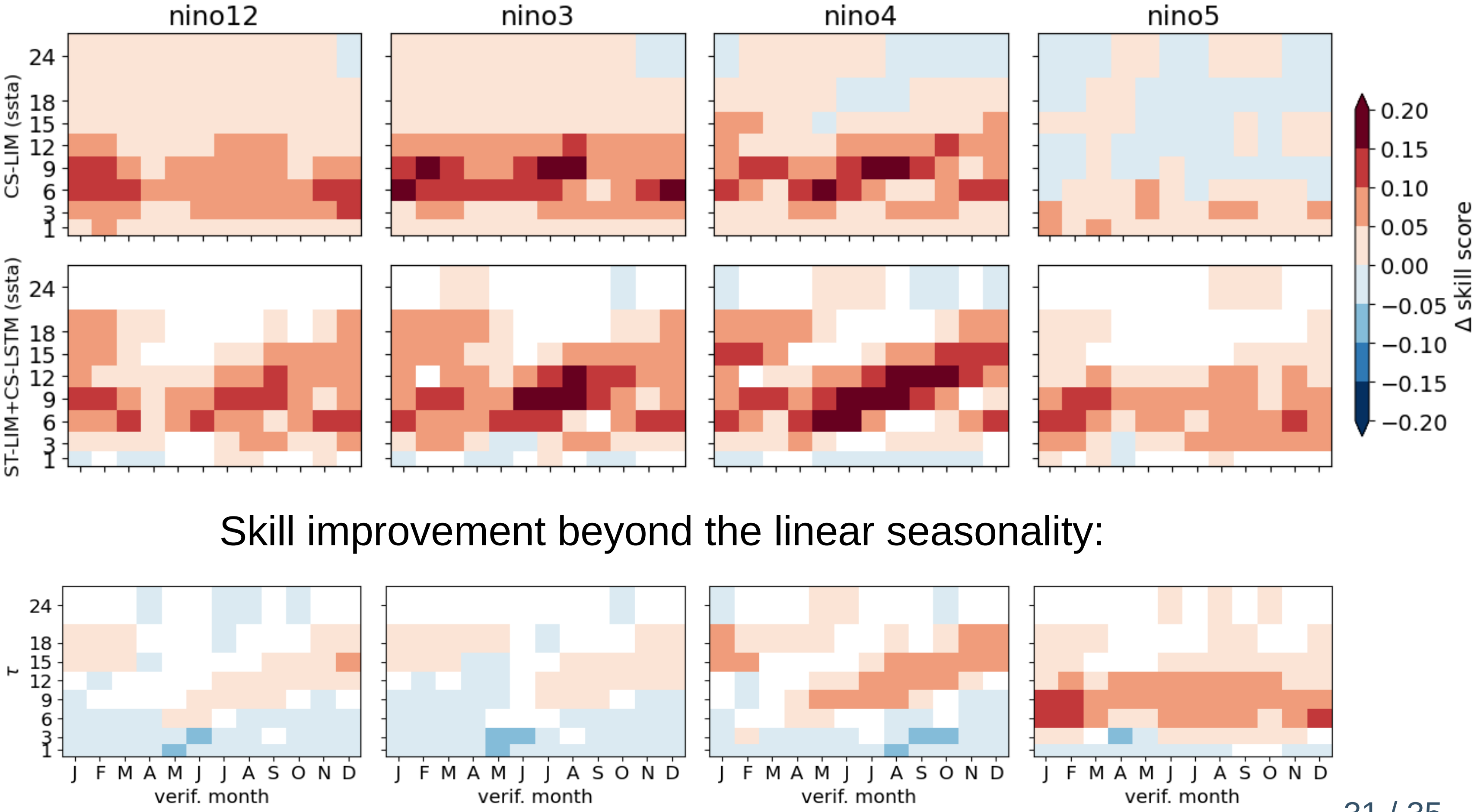
The Seasonal Cycle



The Seasonal Cycle: Skill improvement wrt. ST-LIM

Linear seasonality

?



Skill improvement beyond the linear seasonality:

(ST-LIM+LSTM)
-
CS-LIM

The Ocean Memory

$$\frac{dx}{dt} = \underbrace{F(x(t))}_{\text{deterministic}} + \underbrace{G(x(t))\zeta(t)}_{\text{stochastic}}$$

$$\approx Lx + \underbrace{\mathcal{N}(x)} + \zeta$$

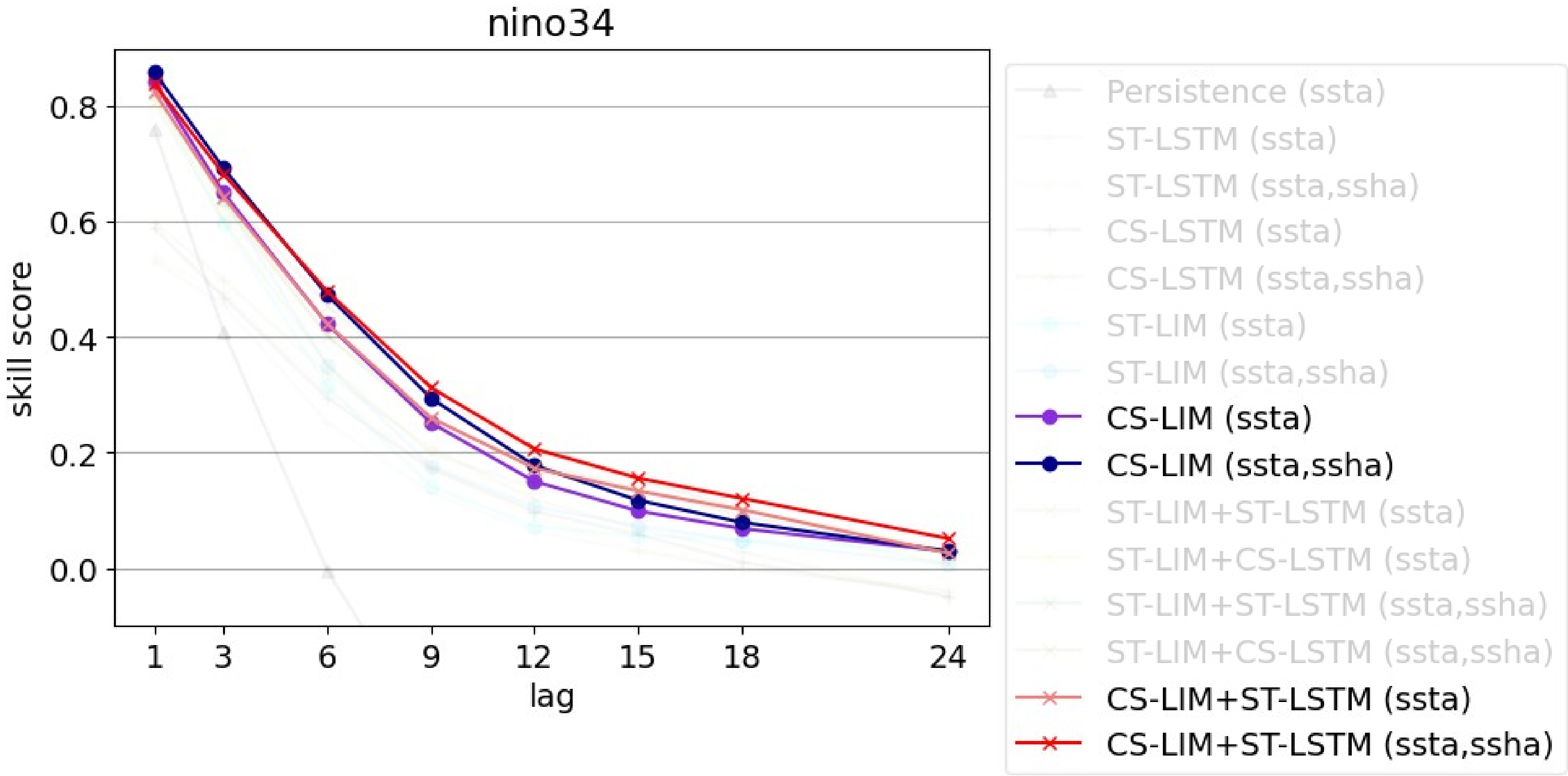
➡ Seasonality: $L_c x + \mathcal{N}_c(x)$

➡ Memory effect:

- Non-Markovianity: $\mathcal{N}_m\left(x(t), x(t-1), \ldots\right)$
- Ocean variables: $x = (\text{ssta}, \text{ssha})$

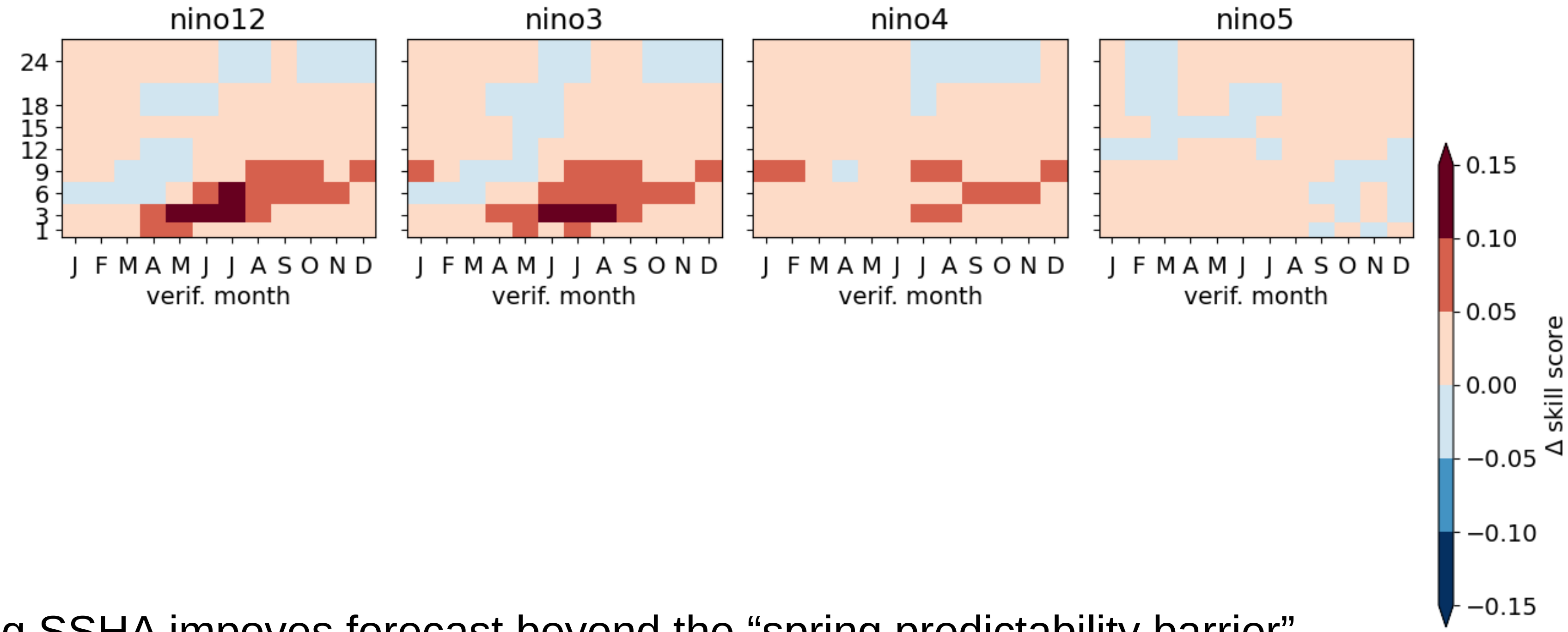
➡ Other nonlinearities

The Ocean Memory



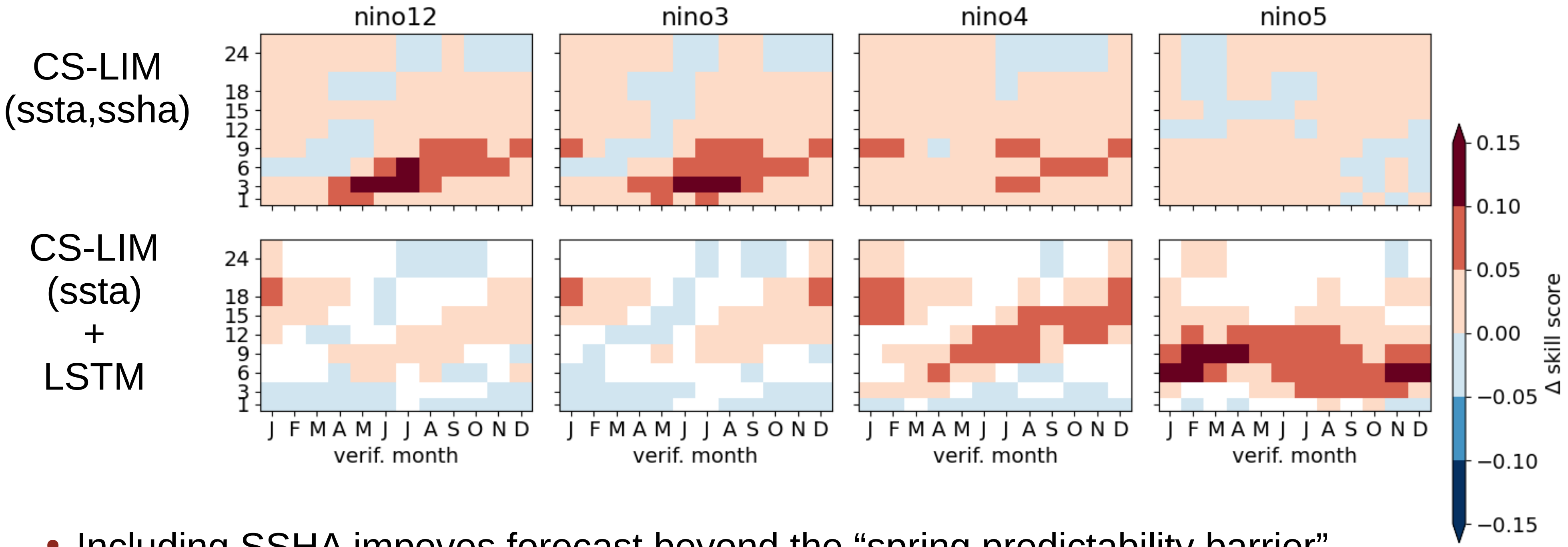
The Ocean Memory: Skill improvement beyond CS-LIM (ssta)

CS-LIM (ssta,ssha)



- Including SSHA impoves forecast beyond the “spring predictability barrier” from 3-9 months mainly in the Eastern Pacific

The Ocean Memory: Skill improvement beyond CS-LIM (ssta)



- Including SSHA impoves forecast beyond the “spring predictability barrier” from 3-9 months mainly in the Eastern Pacific
- LSTM improves forecast from 9-18 months in the Western Pacific