Hybrid Dynamical-Statistical Methods for Climate Downscaling: A Comparison of Methods with examples from the Northeast Pacific

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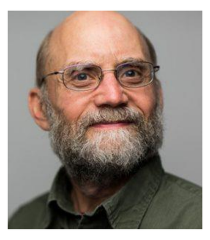
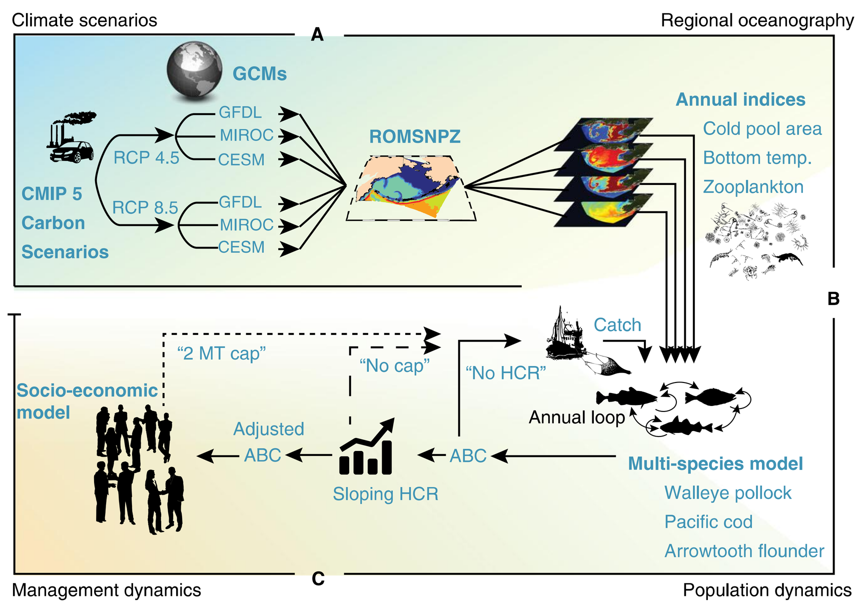


The process of dynamical downscaling entails the use of high-resolution regional models driven by lower resolution global reanalyses and projections. Such regional models, given their higher spatial resolution and sometimes higher biogeochemical detail relative to the global models which drive them, are typically computationally expensive. This expense limits the ultimate size of any downscaled regional ensemble (including parameter sensitivities), which in turn constrains the skill and uncertainty estimates of regional forecasts needed for their effective use in fisheries management. Statistical downscaling based on presently observed correlations between large-scale forcing and small-scale response is an alternate approach, but lacks the ability to capture future emergent behaviors of complex, nonlinear regional biogeochemical systems. Here we describe several alternative techniques for the statistical expansion of dynamically downscaled ensembles. These "hybrid" methods offer a compromise between the spatial, temporal and trophic detail of dynamical methods vs. the numerical efficiency of purely statistical methods. We illustrate several methods, including the use of Machine Learning, with examples from ongoing Management Strategy Evaluation research in the Bering Sea and the Gulf of Alaska.

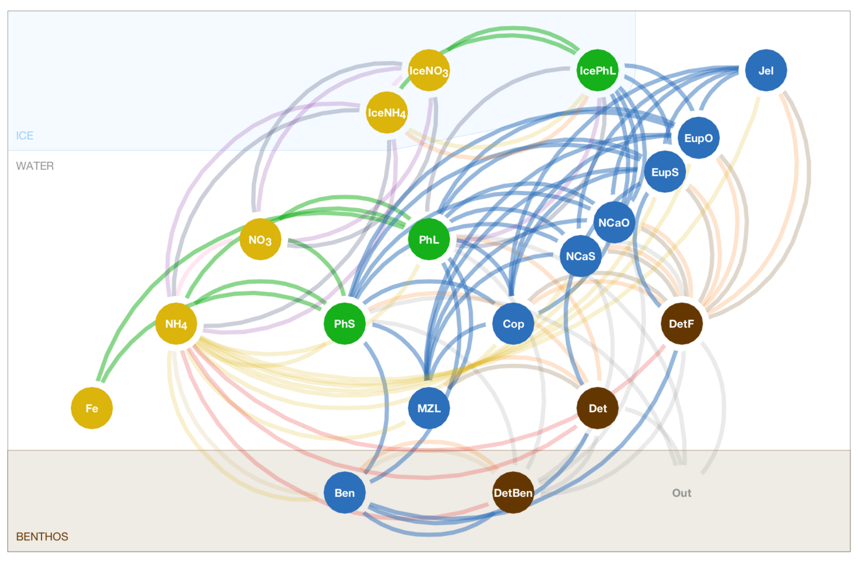
TWO RELATED GOALS OF THESE METHODS:

1) ***SUMMARIZE EMERGENT BEHAVIORS*** of the regional model – what elements rise/fall together in conjunction with the forcing, and what are the spatial patterns?

2) ***APPROXIMATE RESULTS OF DYNAMICAL DOWNSCALING*** - apply a big ensemble of climate projections or seasonal forecasts to the simplified model; get better estimates of means and uncertainty for use in fisheries management



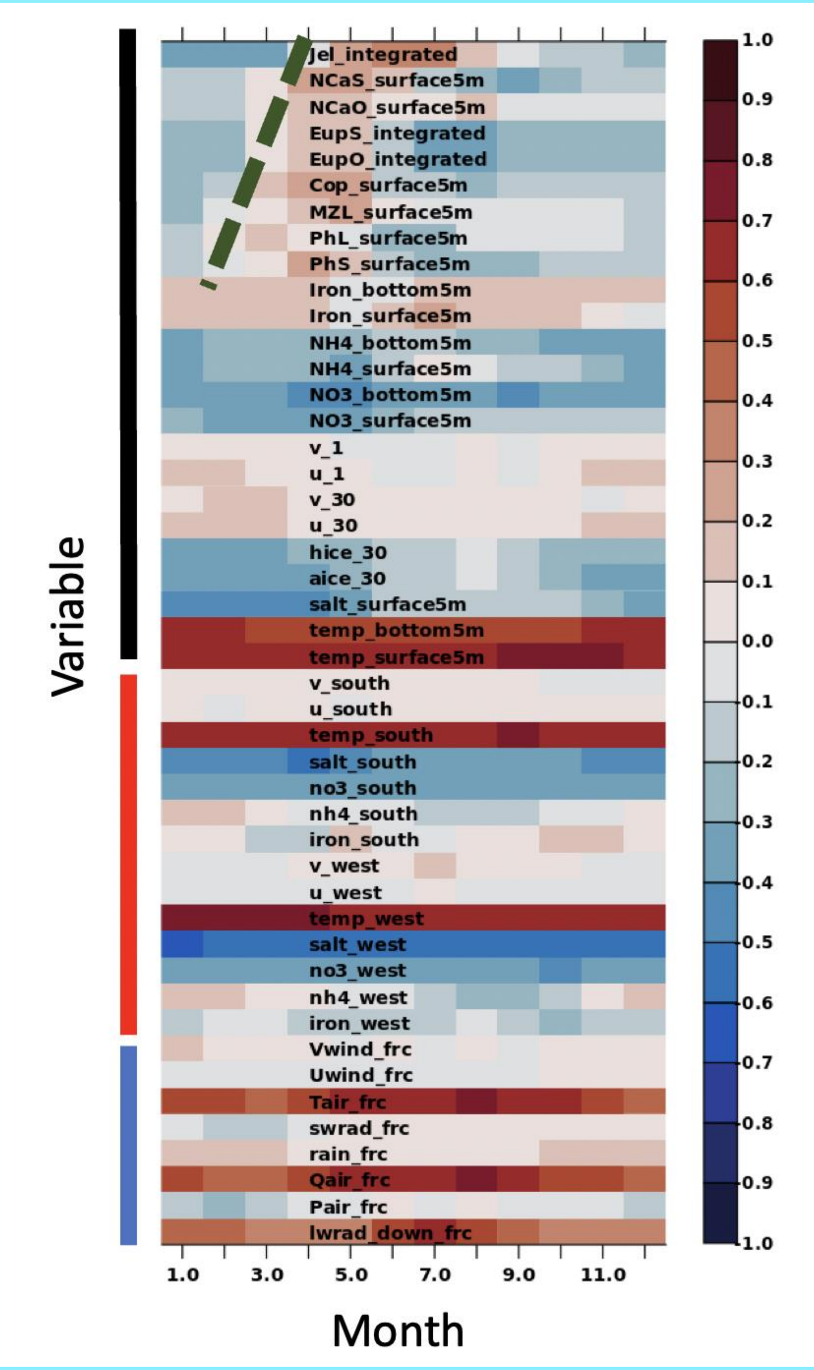
ACLIM program overview of Bering Sea regional model ("ROMSNPZ"), with dynamically downscaled climate projections used for fisheries management



Elements of the NPZ model (from Kearney et al. 2020)

Forcing and response variables used in the multivariate analysis:
GCM atmosphere, GCM ocean, regional ocean response

Jel_integrated	Jellyfish concentration, integrated over depth	mg C m-2
NCaS_surface5m	On-shelf large copepod concentration, surface 5m mean	mg C m-3
NCaO_surface5m	Offshore large copepod concentration, surface 5m mean	mg C m-3
EupS_integrated	On-shelf euphausiid concentration, integrated over depth	mg C m-2
EupO_integrated	Offshore euphausiid concentration, integrated over depth	mg C m-2
Cop_surface5m	Small copepod concentration, surface 5m mean	mg C m-3
MZL_surface5m	Microzooplankton concentration, surface 5m mean	mg C m-3
PhL_surface5m	Large phytoplankton concentration, surface 5m mean	mg C m-3
PhS_surface5m	Small phytoplankton concentration, surface 5m mean	mg C m-3
Iron_bottom5m	iron concentration, bottom 5m mean	micromol Fe m-3
Iron_surface5m	iron concentration, surface 5m mean	micromol Fe m-3
NH4_bottom5m	Ammonium concentration, bottom 5m mean	mmol N m-3
NH4_surface5m	Ammonium concentration, surface 5m mean	mmol N m-3
NO3_bottom5m	Nitrate concentration, bottom 5m mean	mmol N m-3
NO3_surface5m	Nitrate concentration, surface 5m mean	mmol N m-3
v_1	Along-shelf velocity, bottom layer	m s-1
u_1	Cross-shelf velocity, bottom layer	m s-1
v_30	Along-shelf velocity, top layer	m s-1
u_30	Cross-shelf velocity, top layer	m s-1
hice_30	average ice thickness in cell	m
aice_30	fraction of cell covered by ice	(no units)
salt_surface5m	salinity, surface 5m mean	psu
temp_bottom5m	potential temperature, bottom 5m mean	Celsius
temp_surface5m	potential temperature, surface 5m mean	Celsius
v_south	Along-shelf velocity at southeastern boundary, top layer	m s-1
u_south	Cross-shelf velocity at southeastern boundary, top layer	m s-1
temp_south	potential temperature at southeastern boundary, top layer	Celsius
salt_south	Salinity at southeastern boundary, top layer	psu
no3_south	Nitrate at southeastern boundary, top layer	mmol N m-3
nh4_south	Ammonium at southeastern boundary, top layer	mmol N m-3
iron_south	iron at southeastern boundary, top layer	micromol Fe m-3
v_west	Along-shelf velocity at southwestern boundary, top layer	m s-1
u_west	Cross-shelf velocity at southwestern boundary, top layer	m s-1
temp_west	potential temperature at southwestern boundary, top layer	Celsius
salt_west	Salinity at southwestern boundary, top layer	psu
no3_west	Nitrate at southwestern boundary, top layer	mmol N m-3
nh4_west	Ammonium at southwestern boundary, top layer	mmol N m-3
iron_west	iron at southwestern boundary, top layer	micromol Fe m-3
Vwind_frc	Northward wind from global model	m s-1
Uwind_frc	Eastward wind from global model	m s-1
Tair_frc	Air temperature from global model	Celsius
swrad_frc	Shortwave radiation from global model	Watts m-2
rain_frc	Rainfall from global model	m s-2
Qair_frc	Absolute humidity from global model	g g-1
Pair_frc	Surface air pressure from global model	Pa
lwrad_down_frc	Downwelling longwave radiation from global model	Watts m-2



Dominant multivariate factor illustrates how strongly different variables are connected to each other, and across different months of the year. Deep colors indicate a strong contribution to the factor. Dotted line highlights a trophically arrayed shift in phenology

Method 1: use spatial EOFs of forcing and response variables to derive multivariate structure at the *pattern* level; use these to approximate the full dynamical response to other GCMs or emission scenarios

Steps in method 1:

1) From dynamically downscaled GCM output, calculate spatial EOFs of monthly anomalies for each biophysical variable **and** each month of the year.

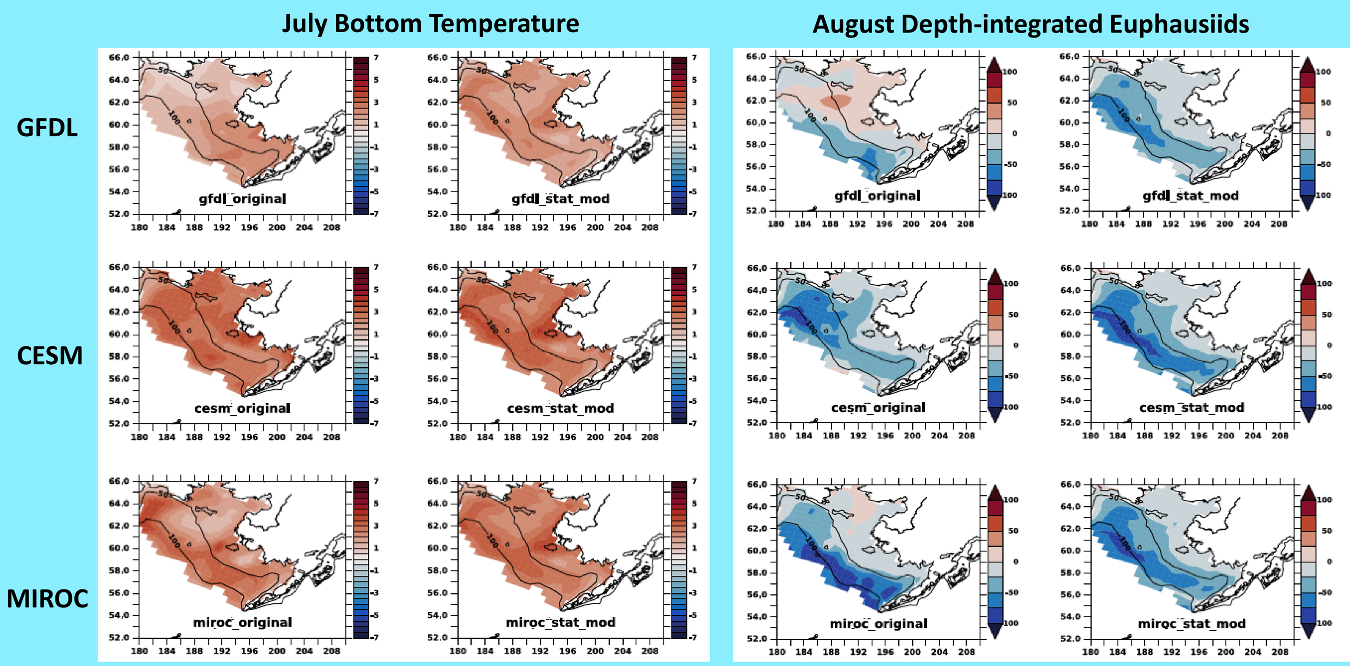
This yields:

a) A set of spatial patterns (the EOFs in the original units of that variable) for that month

b) A set of time series modulating those spatial patterns (the PCs, which have unit variance)

2) Perform a second PC analysis on those time series (2b) to seek multivariate "factors" (i.e. *temporally correlated multivariate spatial patterns*) relating the forcing to the biophysical response.

3) Project atmospheric/oceanic forcing from other GCMs onto the derived multivariate spatial patterns. This yields a much larger ensemble of estimates for each regional biophysical variable.

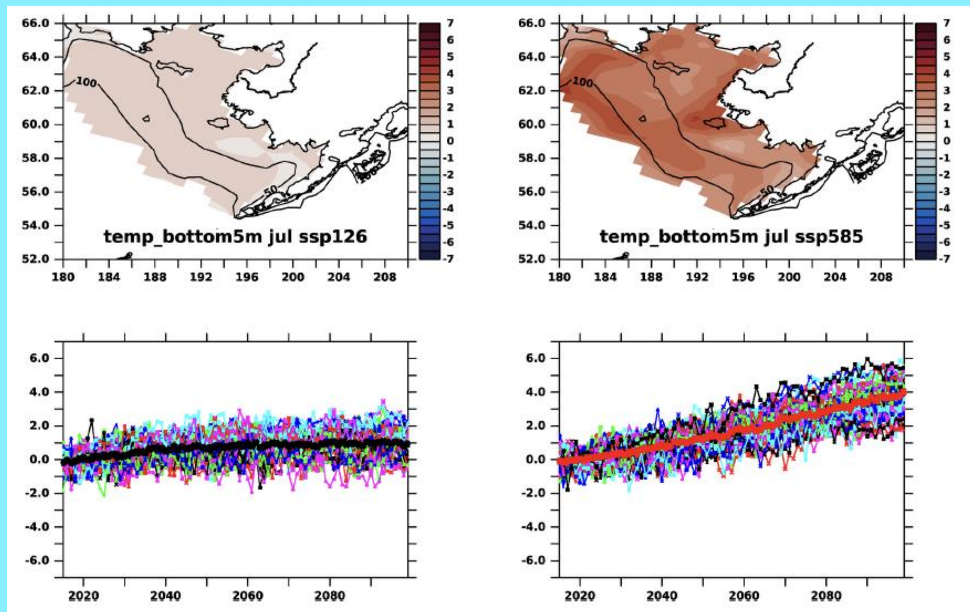


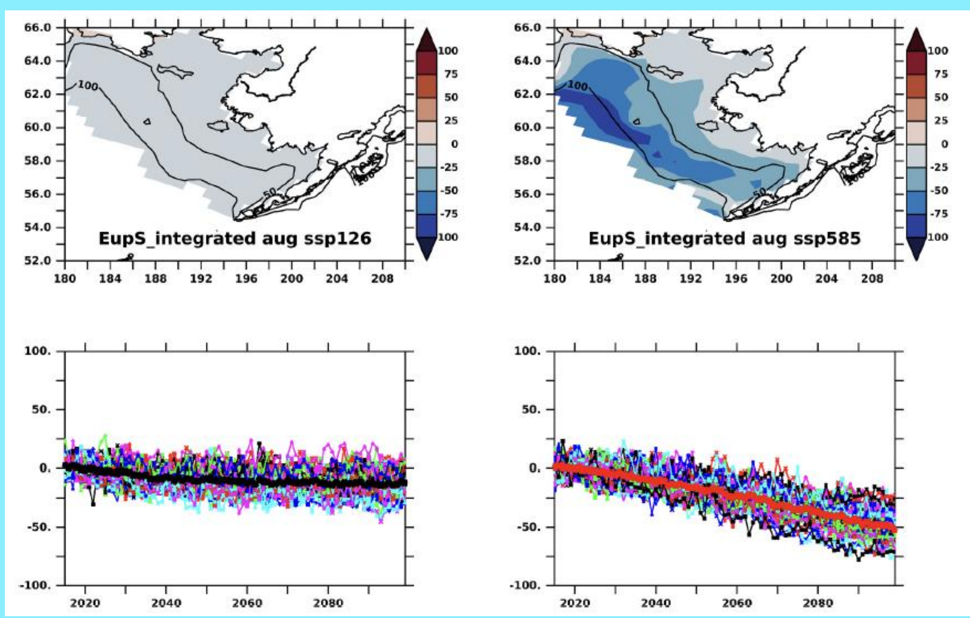
The statistical-dynamical hybrid method ("stat") captures most of the full dynamical downscaling signal ("original") on the Bering Sea shelf: here compare *change* in 30-year averages (2015-2044 -> 2070-2099) under ssp585 scenario forcing from three GCMs (GFDL, CESM, MIROC)

More details HERE!

CMIP6 monthly analysis

CMIP5 yearly analysis





Projection of the forcing from 28 additional GCMs yields estimates of regional change in bottom temperatures and euphausiids over the 21st century under two different emission scenarios. Spatial patterns show ensemble average of projected change in 30-year averages between 2015-2044 and 2070-2099, under ssp126 (left) and ssp585 (right). Time series show evolution of individual realizations (thin lines) and evolution of the mean (thick lines).

DISCUSSION

Many potential methods for climate downscaling. In addition to spatially localized skill, we seek to minimize artifacts which violate mass conservation (e.g. discontinuities in space **or** across trophic levels).

Method 1 could be considered an extension of **Linear Inverse Modeling**. In typical usage, a **LIM** uses lagged correlations to predict future states based on the present state plus unknowable future noise. Here we are predicting regional results based on present, past, and *future* (within one year) states of global forcing.

Method 2-LM, seeks out simple linear relationships between present forcing and present response. In method **2-LSTM**, as in **LIM**, we allow for past forcing and response to influence the present state.

NEXT STEPS: attempt LSTM using **full dynamically downscaled output**, rather than the dimensionally reduced (EOF) version.

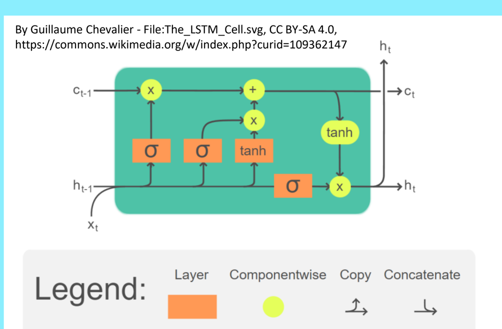
As in method 1, our first step is dimensional reduction. For selected variables, we calculate **univariate** EOFs and PCs from monthly anomalies. We then seek to relate the forcing PCs (predictors) to the response PCs (predictand)

Forcing variables used as predictors:

- Air Temperature (Tair_frc)
- Zonal wind (Uwind_frc)
- Meridional wind (Vwind_frc)
- Southeastern boundary SST (temp_south)
- Southwestern boundary SST (temp_west)

Response variable to be predicted:

- Shelf bottom temperature (temp_bottom5m)



Overview of the LSTM method, which optimizes the use of present and past states of the system (both forcing and response) to best predict the evolving response variable(s)

Method 2: Multivariate Linear Regression (LM) and Computational Neural Network (Long-Short Term Memory network; LSTM) are trained to relate the dominant PCs (time series) of the forcing variables to the dominant PC of the response variable. As in method 1, the trained model could be used to predict the full nonlinear model response to a large ensemble of projected forcing.

LM model:

*Temp_bottom5m = c1*Tair_frc + c2*Uwind_frc + c3*Vwind_frc + c4*temp_west + c5*temp_south + c6*

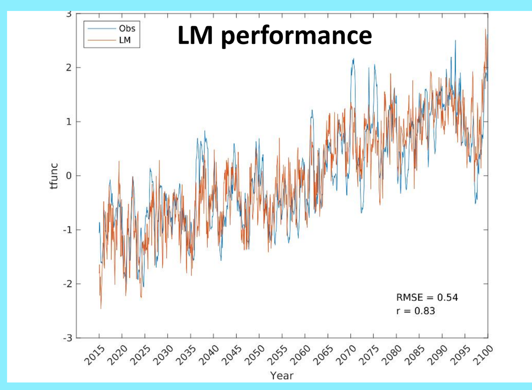
TRAINING SET

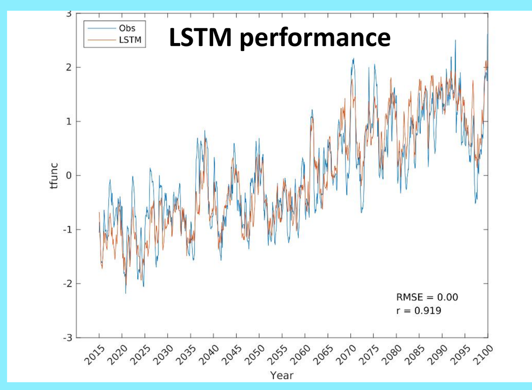
	CESM+GFDL	MIROC+CESM	MIROC+GFDL
Tair_frc	0.3601	0.3459	0.3197
Uwind_frc	0.1269	0.1109	0.1366
Vwind_frc	-0.0441	-0.0075	-0.0202
temp_west	-0.0715	0.0638	0.1408
temp_south	0.6181	0.5758	0.4020

Fraction of variance in bottom temperature explained by various forcing terms in LM model, trained using three different subsets of the dynamically downscaled output

CESM		GFDL		MIROC	
ssp126	ssp585	ssp126	ssp585	ssp126	ssp585
0.8075	0.9092	0.6457	0.8308	0.5920	0.8732
0.8873	0.9271	0.8227	0.9192	0.8289	0.9443

Comparison of r-values (goodness of fit to response variable) for LM-trained (blue) vs. LSTM- trained (red) models. In each case, LSTM outperforms LM in fitting the response data





Time series comparison of predictions from trained models (red) vs independent dynamical model output (blue). In this example, models were trained on downscaled CESM and MIROC ssp585 results and tested using GFDL ssp585 results. Upper panel shows performance of LM model; lower panel shows superior performance of LSTM model (higher r, lower RMSE)