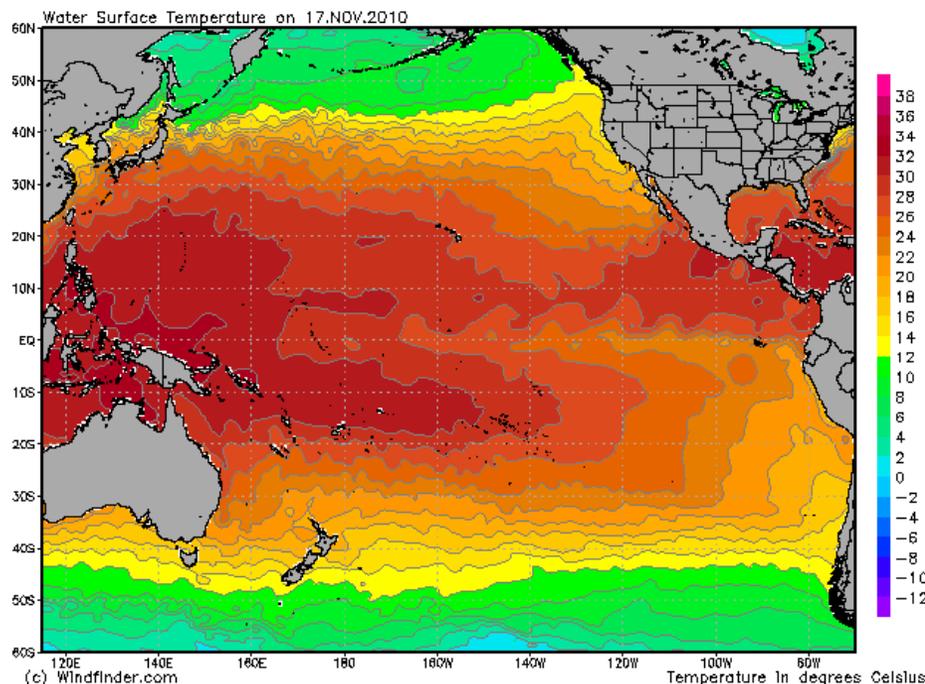


基于物理和深度学习的海洋-大气耦合模式 及其在 ENSO 研究中的应用

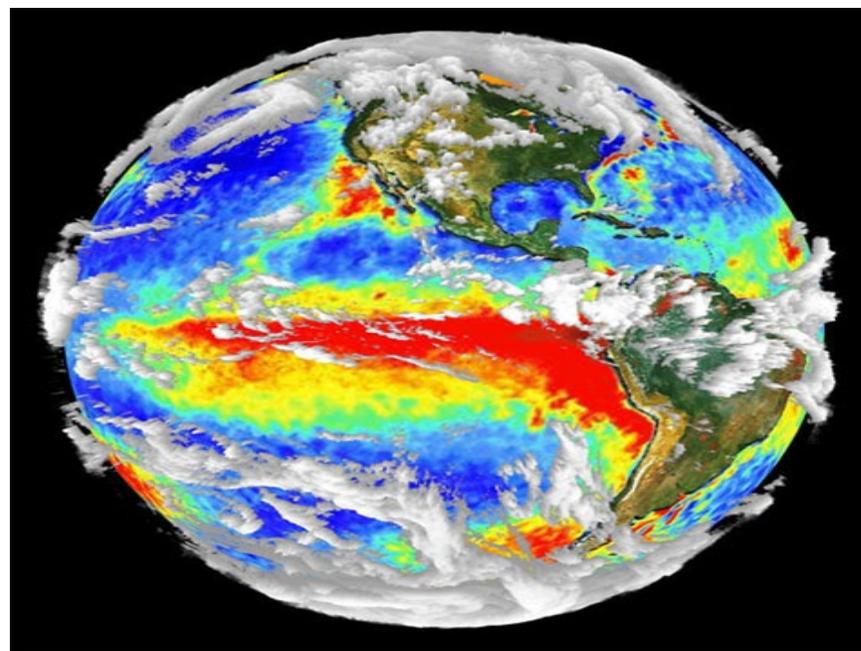
张荣华 周路 高川 杜双盈 朱聿超
南京信息工程大学海洋科学学院等

天气预报

太平洋海表温度 (SST) 平均气候态分布



1997年12月SST年际异常: **El Nino**



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1 研究背景

2 基于物理的 ENSO 模式及预测

3 基于 Transformer 的 ENSO模型

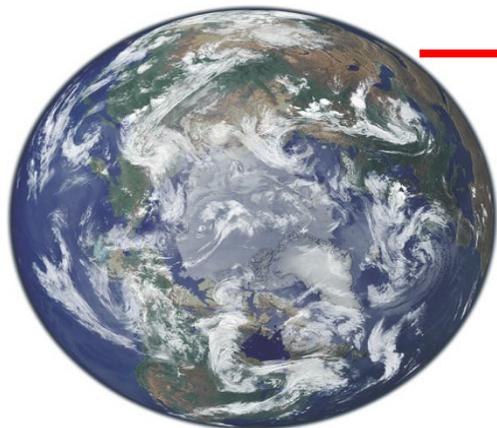
4 物理模式和数据驱动模型的融合

物理模式中引入深度学习 (DL) 方法

DL模型中引入物理模式 (约束)

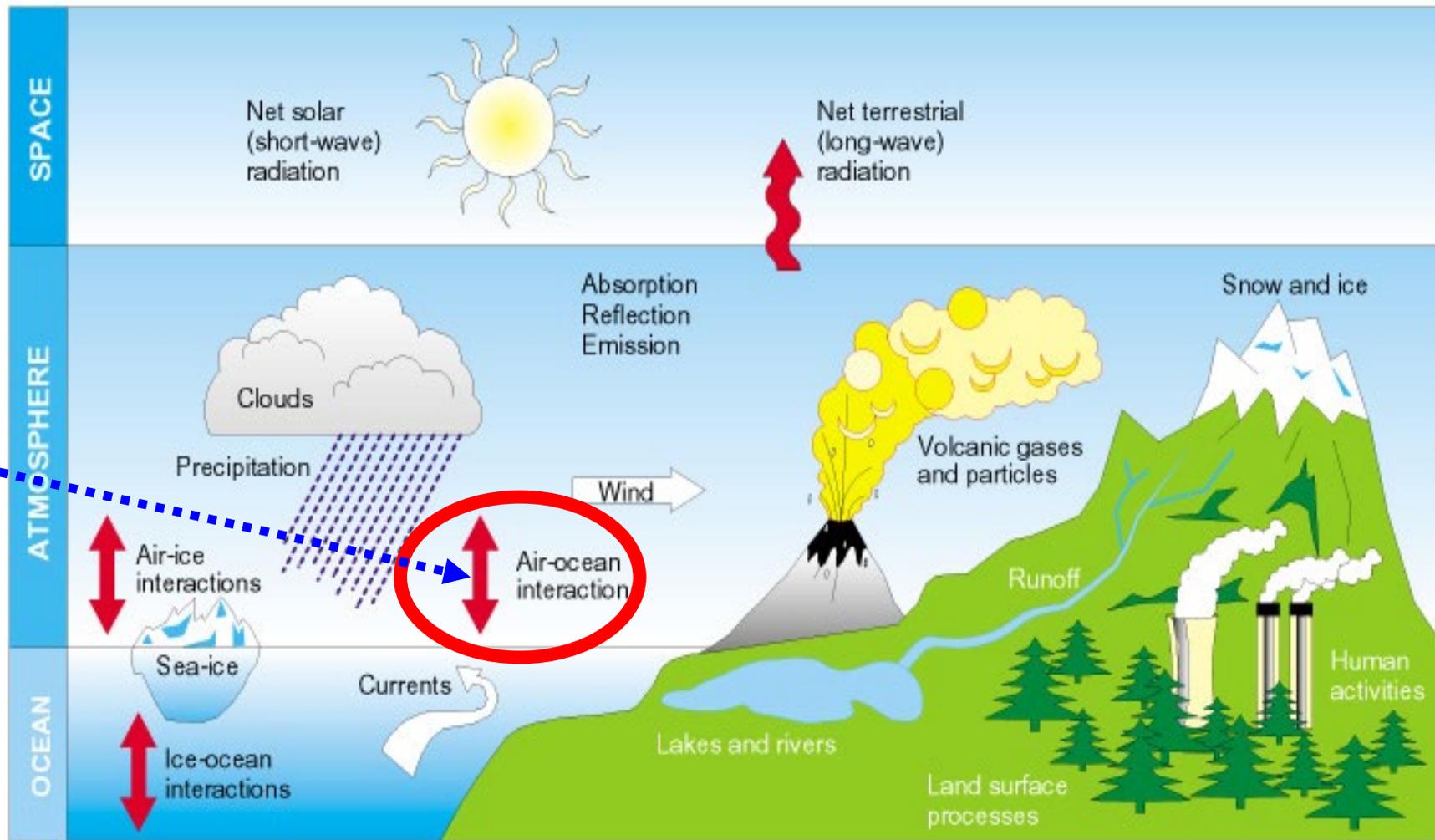
5 总结与讨论

地球系统



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The Climate System



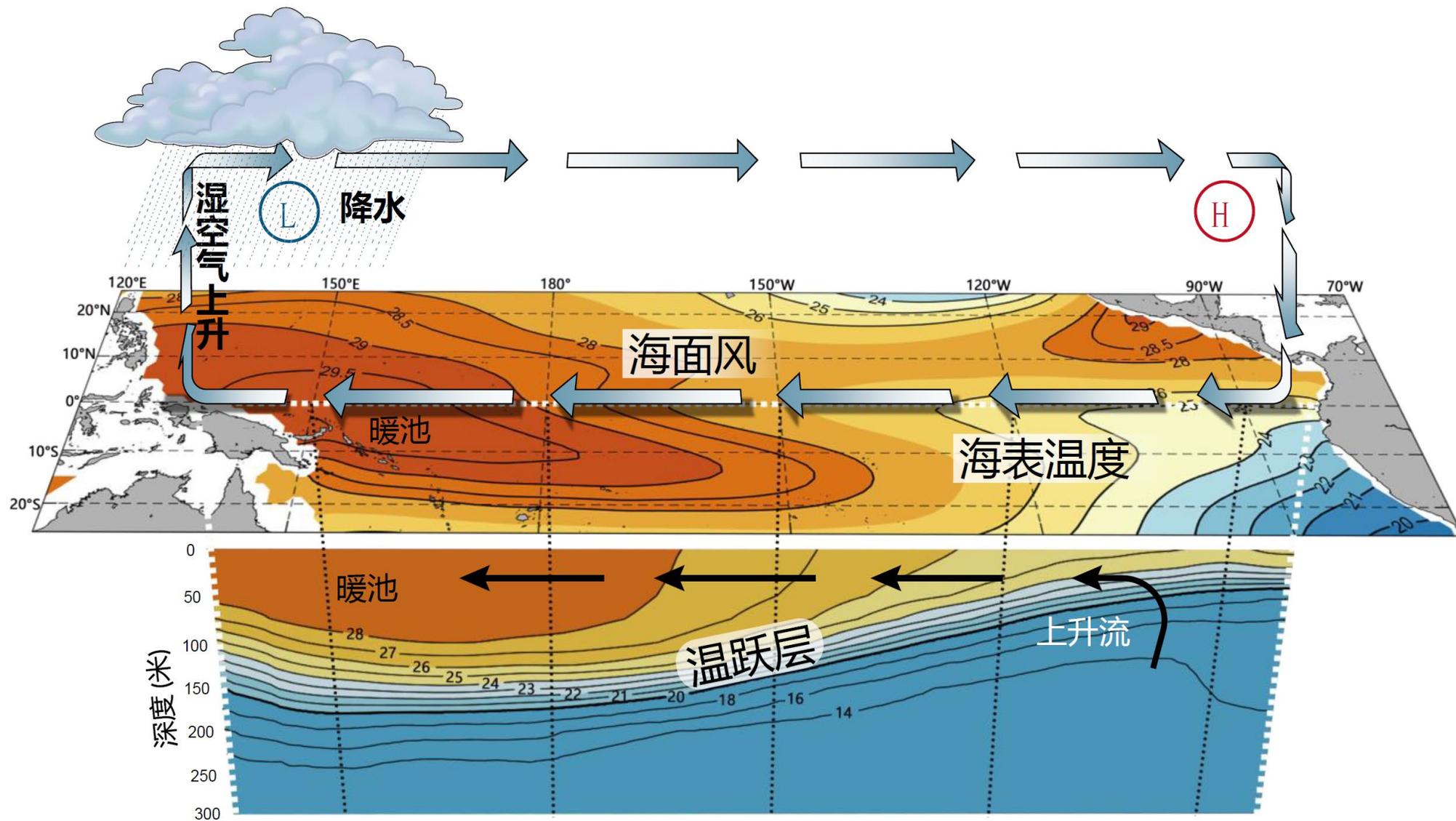
海气相互作用：海洋变化对大气产生影响，所产生的响应异常又反过来对海洋产生影响，这种相互影响过程为海洋-大气相互作用，是一种海气异常得以发展和加强的基本过程，造就了各种现象

。 。 。

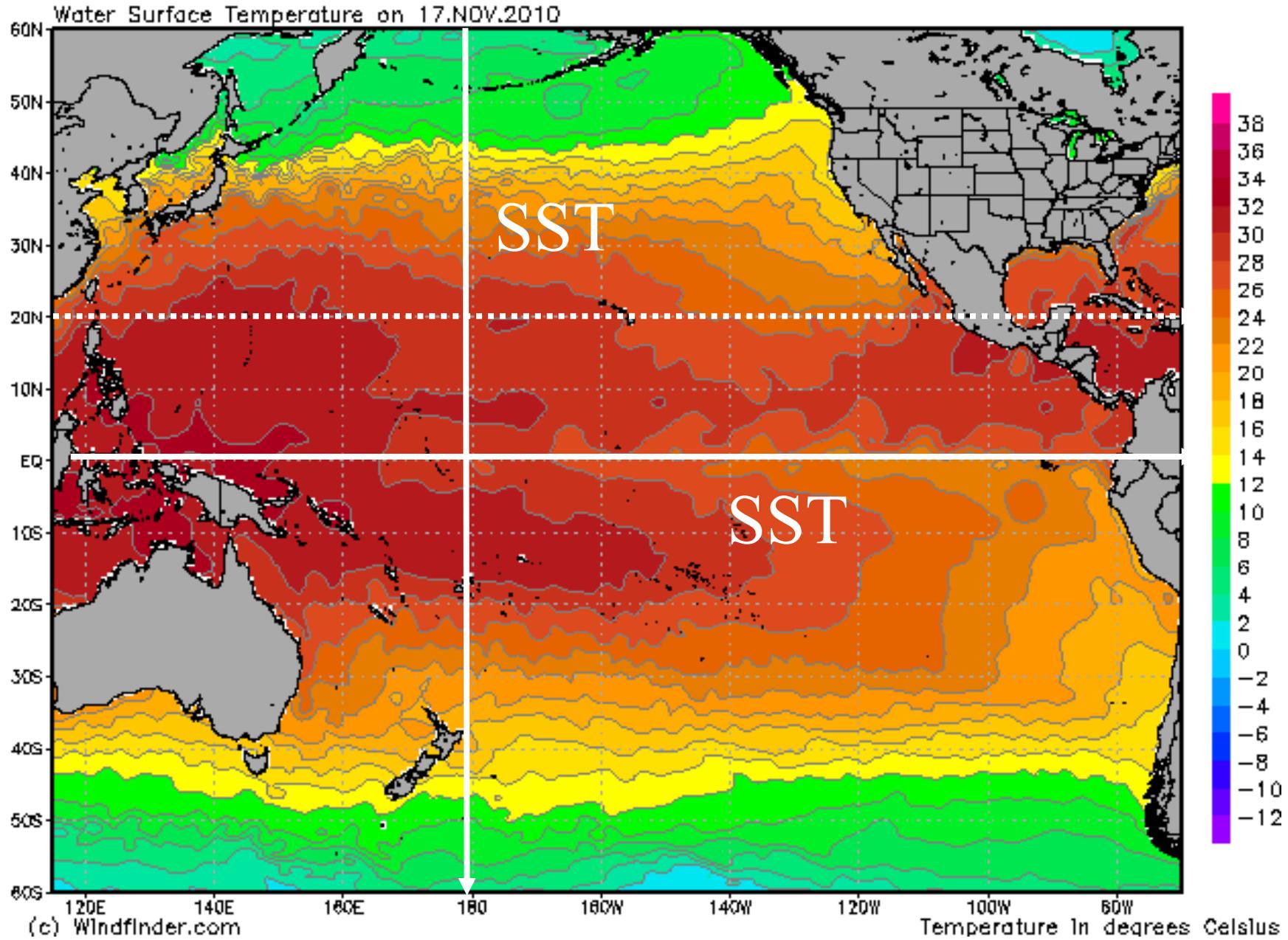
表现形式：观测到的现象、过程、信号等。归来为起源于大气、海洋或海气相互作用。

courtesy N. Noreiks, L. Bengtsson, MPI

热带太平洋海气相互作用现象和过程



Pacific sea surface temperature



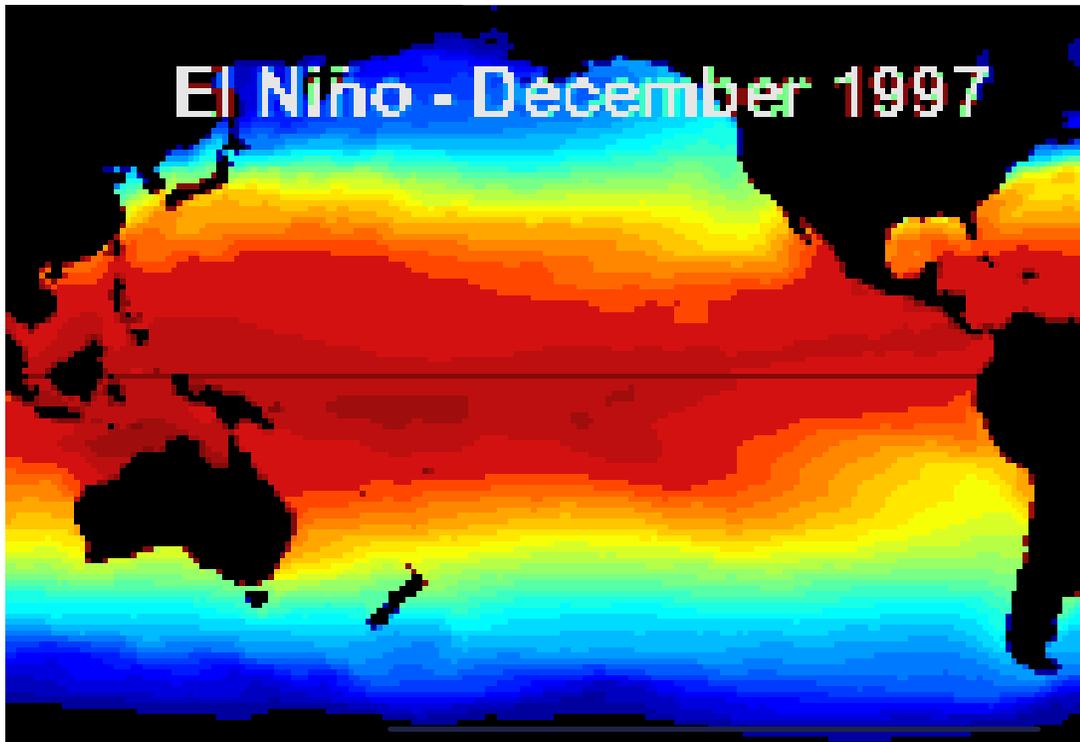
El Nino-Southern Oscillation (ENSO)

Sea surface temperature (SST) anomalies

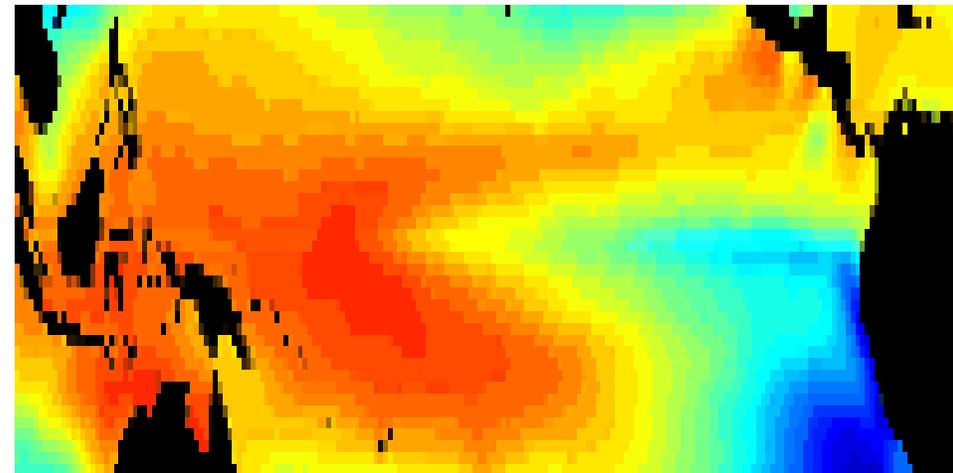
El Nino (La Nina): SST warm (cold) anomalies in the eastern equatorial Pacific at intervals of 3-7 years; the strongest interannual signal in the climate system; basinwide ocean-atmosphere interactions; most predictable signals

ENSO effects:
teleconnections

El Nino : 1997/12



La Nina :1998/12

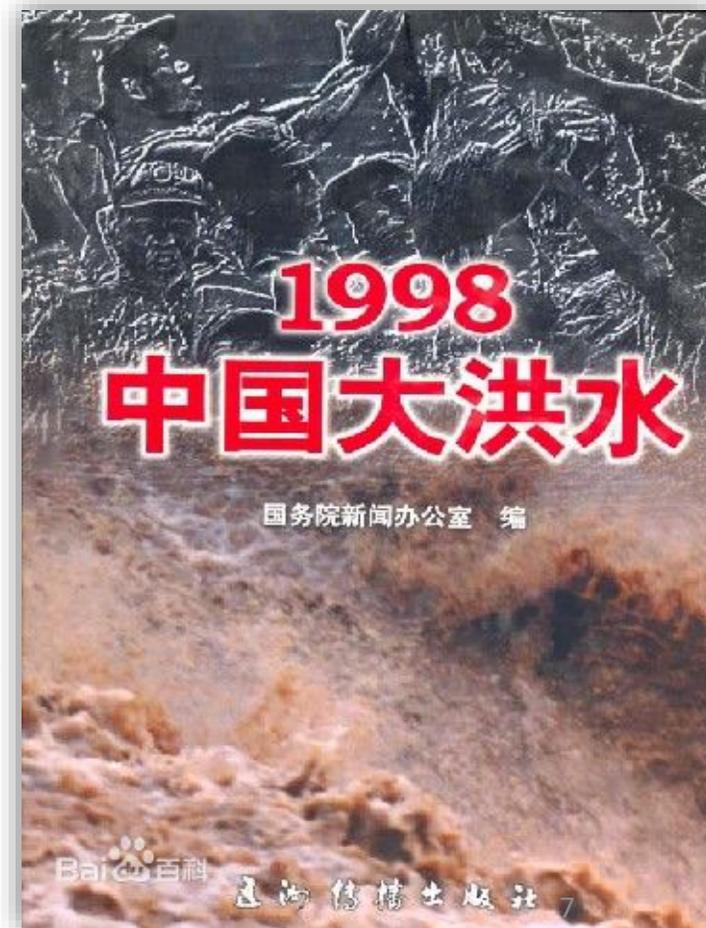
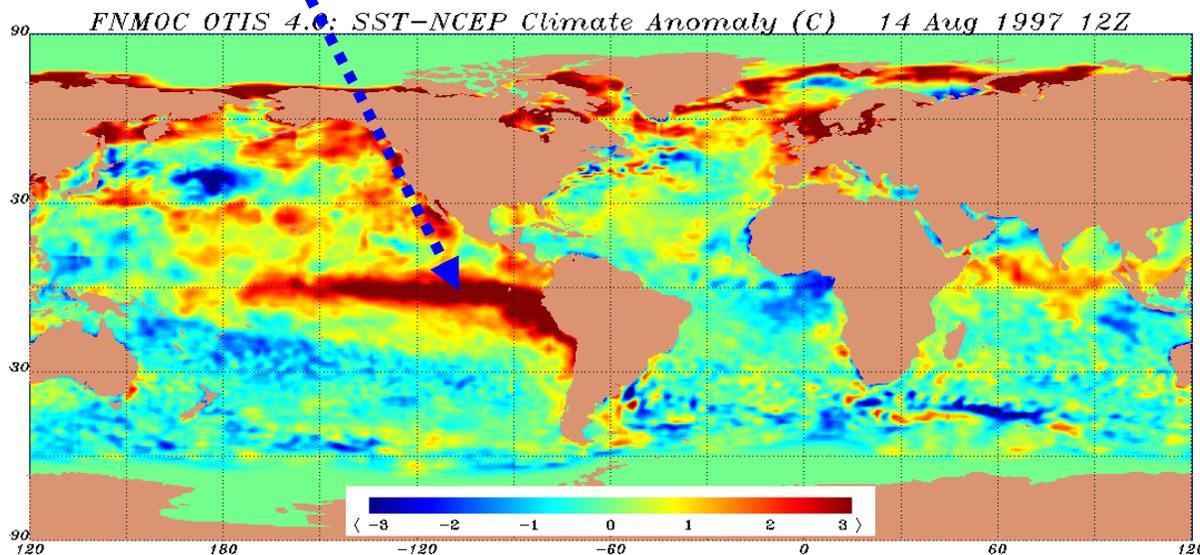


1. 研究背景

厄尔尼诺-南方涛动 (ENSO): 实时预测 \Longrightarrow 年际气候异常预测

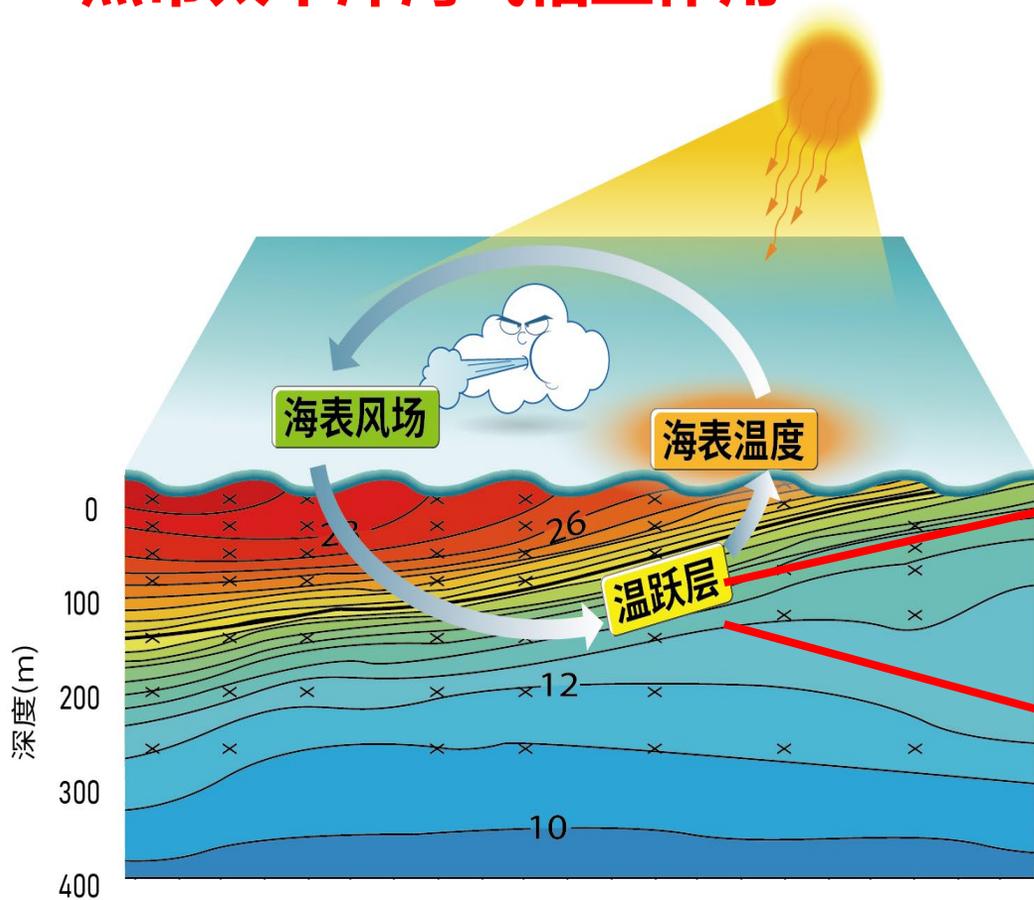
ENSO 是气候系统中最强的年际变化信号，通过大气遥相关过程，对全球天气、气候产生重大影响，也对环境和社会产生深远影响。ENSO 奠定了短期气候预测的基础，具有巨大的经济和社会价值。但目前 ENSO 变异机制还认识不足，对其实时预测还存在着巨大的挑战

1997年8月
海表温度
(SST) 异常

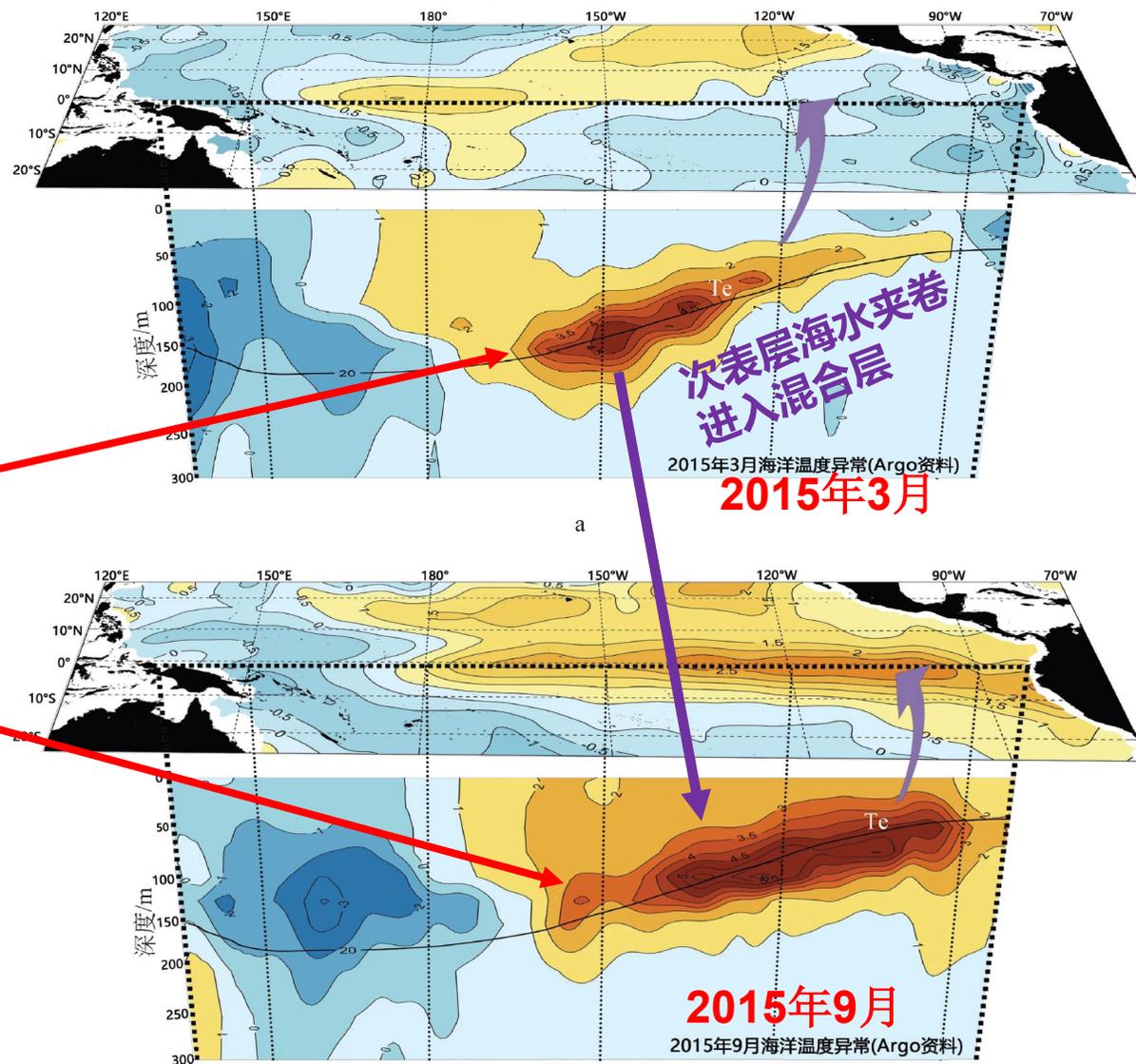


表征ENSO 相关主要过程：次表层热力异常时空演变及其对海表温度的影响

热带太平洋海气相互作用



次表层异常三维 (3D) 演变及对SST影响



大气

海洋

风应力 (τ) 热通量 (Q_T) 淡水通量 (Q_S)

海表面温度(SST)

$$\begin{cases} \frac{\partial u}{\partial t} + u \frac{\partial u}{\partial x} + v \frac{\partial u}{\partial y} + w \frac{\partial u}{\partial z} = -\frac{1}{\rho} \frac{\partial p}{\partial x} + f v + F_x \\ \frac{\partial v}{\partial t} + u \frac{\partial v}{\partial x} + v \frac{\partial v}{\partial y} + w \frac{\partial v}{\partial z} = -\frac{1}{\rho} \frac{\partial p}{\partial y} - f u + F_y \\ -\frac{1}{\rho} \frac{\partial p}{\partial z} - g = 0 \end{cases}$$

$$F_x = \frac{\partial}{\partial z} \left(\nu_v \frac{\partial u}{\partial z} \right)$$

$$z = 0, \quad \nu_v \frac{\partial u}{\partial z} = \tau_{zx} = \rho c_D |V| u$$

$$z = 0, \quad \nu_v \frac{\partial v}{\partial z} = \tau_{zy} = \rho c_D |V| v$$

$$z = 0, \quad k_v \frac{\partial T}{\partial z} = \text{Heat flux}$$

$$z = 0, \quad k_v \frac{\partial S}{\partial z} = \text{Freshwater flux}$$

$$\frac{\partial u}{\partial x} + \frac{\partial v}{\partial y} + \frac{\partial w}{\partial z} = 0$$

$$F_T = \frac{1}{\rho c_p} \frac{\partial}{\partial z} \left(k \frac{\partial T}{\partial z} \right)$$

$$\begin{cases} \frac{\partial T}{\partial t} = -u \frac{\partial T}{\partial x} - v \frac{\partial T}{\partial y} - w \frac{\partial T}{\partial z} + Q_T / (\rho C_p) + F_T \\ \frac{\partial S}{\partial t} = -u \frac{\partial S}{\partial x} - v \frac{\partial S}{\partial y} - w \frac{\partial S}{\partial z} + Q_S S_0 + F_S \end{cases}$$

$$\rho = \rho(T, S, p)$$

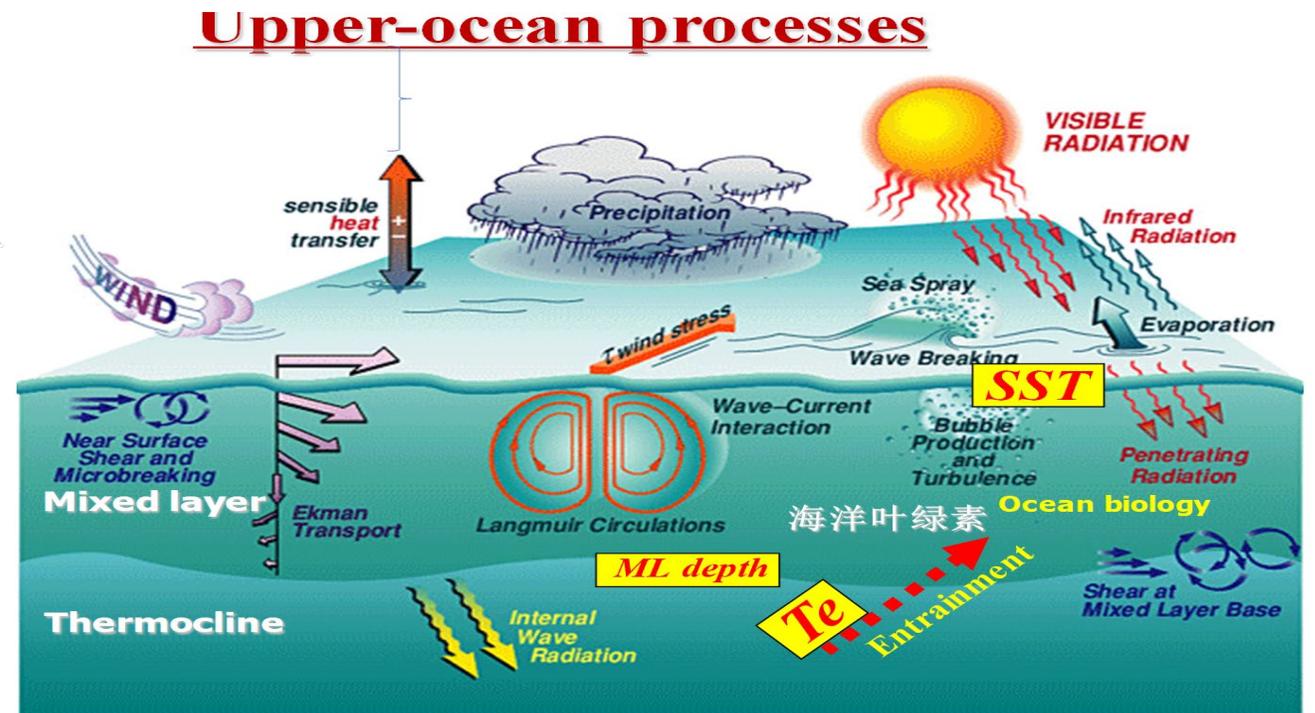
与 ENSO 相关海气耦合模式构建及应用

模式属性:

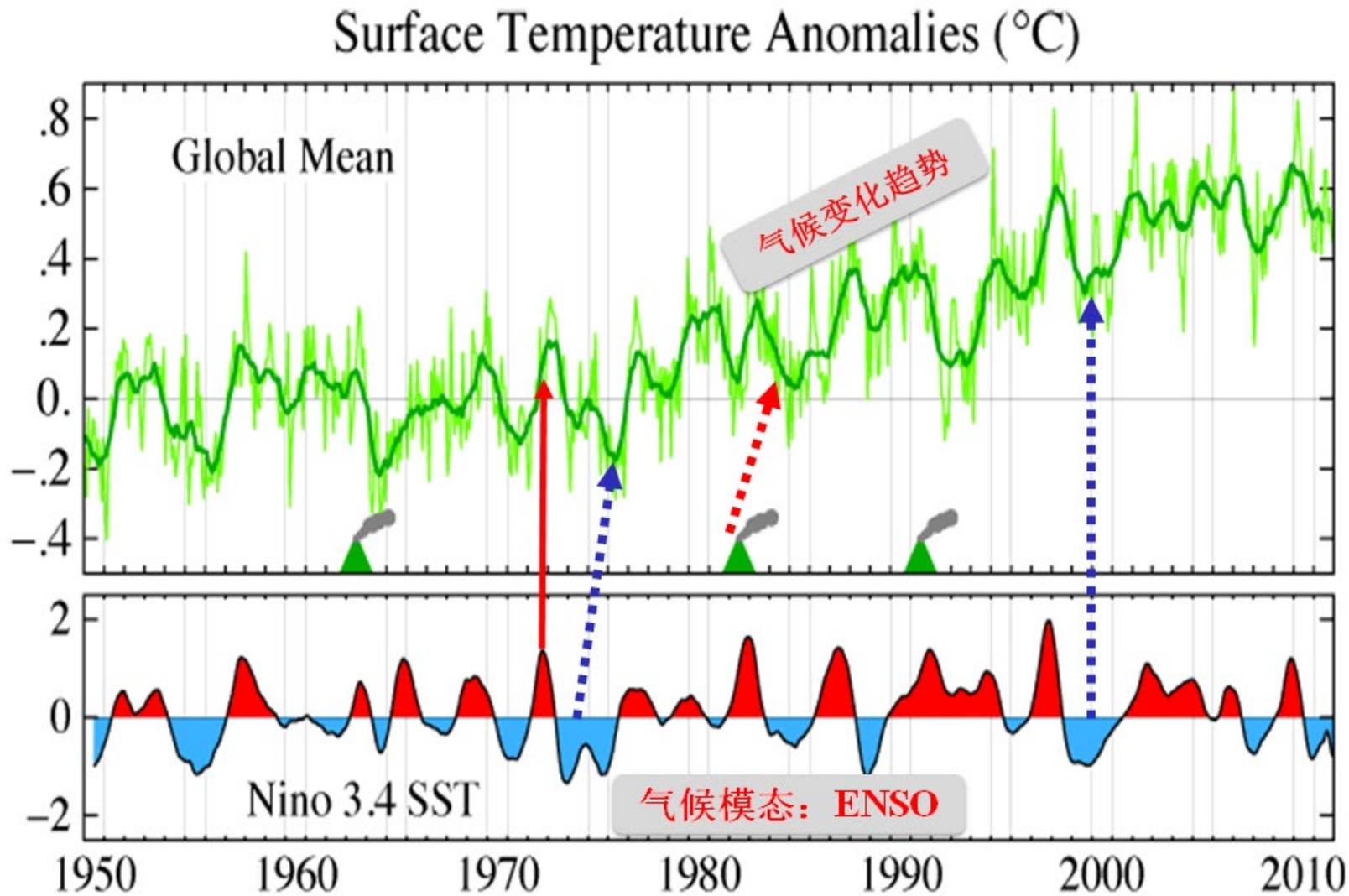
- ✓ 动力框架: 原始方程; 垂直坐标; 动力简化 (如垂直模分解); level & layer model; ...
- ✓ 过程表征:
- ✓ 计算实现

比较、认知和改进

模拟对模式的强烈依赖性?

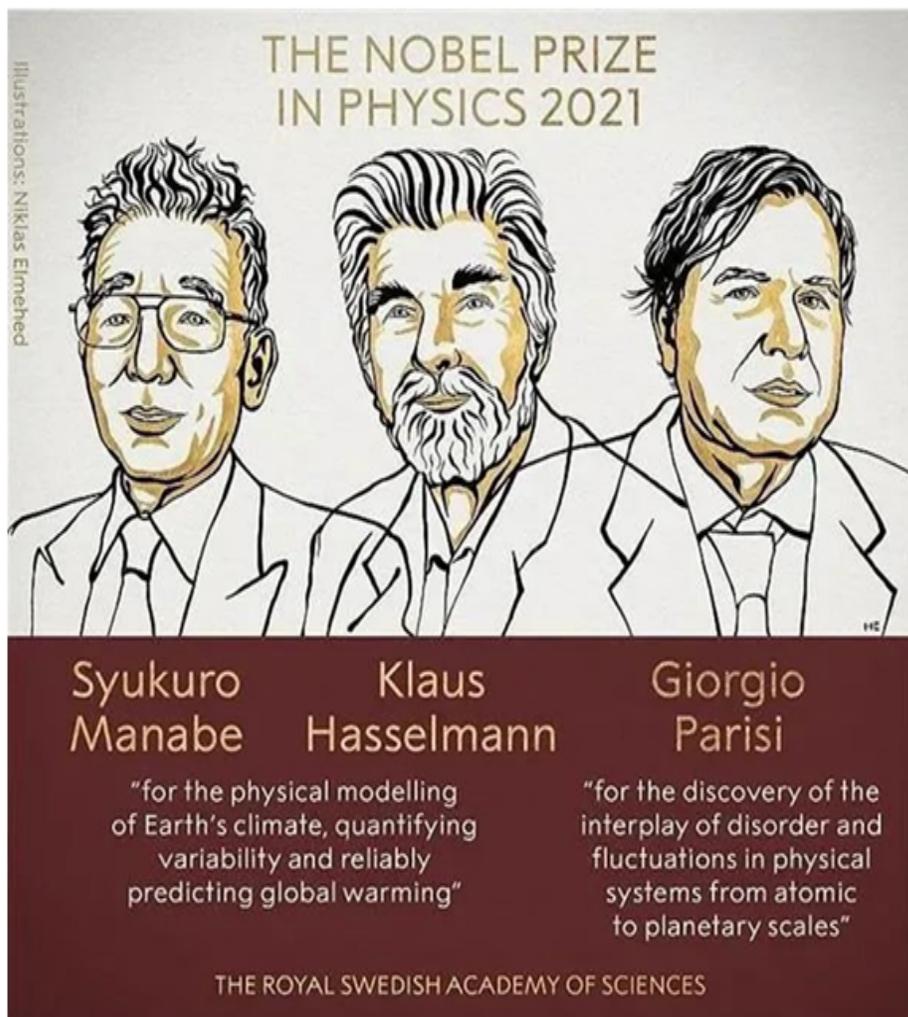


地球系统模式应用：气候变化与 ENSO 等研究



2021年诺贝尔物理学奖：其中两位是气候学家

Syukuro Manabe、Klaus Hasselmann 和 Giorgio Parisi



对地球气候的物理建模、
量化可变性并对全球变暖
进行可靠预测

Manabe 的主要贡献：

1. 第一代全球气候模式

考虑了多圈层相互作用，包括水循环对加热大气的贡献。

2. Manabe的辐射对流平衡模式

辐射平衡与对流热通量间相互作用

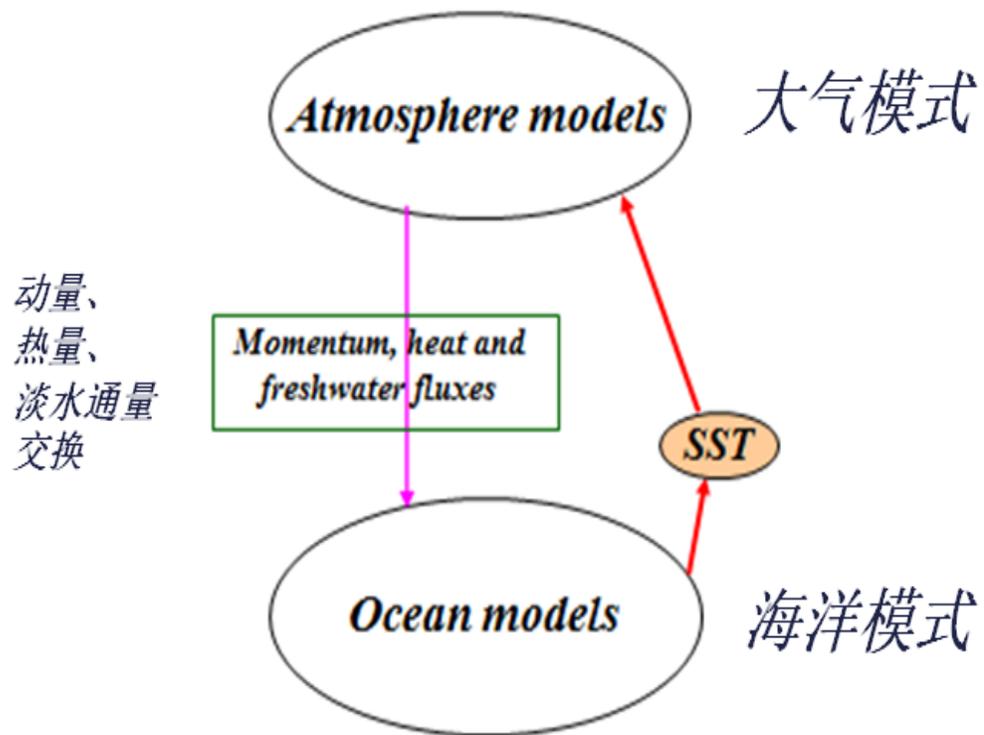
3. 二氧化碳与温室效应

模拟随着 CO₂浓度变化的大气温度变化，如随着二氧化碳的加倍，地表平均温度将会上升约 2.4°C。

基于动力过程的 ENSO 模式

海气耦合模式

Coupled ocean-atmosphere models
(ICMs, HCMs and CGCMs)



- 概念模式
- 中间型耦合模式 (ICMs)
- 混合型耦合模式 (HCMs)
- 耦合环流模式 (CGCMs)

A review of progress in coupled ocean-atmosphere model developments for ENSO studies in China*

ZHANG Rong-Hua^{1,2,3,4,**}, YU Yongqiang^{4,5}, SONG Zhenya^{6,7,8,9}, REN Hong-Li^{10,11},
TANG Youmin^{12,13}, QIAO Fangli^{6,7,8,9}, WU Tongwen¹⁴, GAO Chuan^{1,2}, HU Junya^{1,2},
TIAN Feng^{1,2}, ZHU Yuchao^{1,2}, CHEN Lin^{5,14}, LIU Hailong⁵, LIN Pengfei⁵,
WU Fanghua¹⁵, WANG Lin^{10,11}

¹ Key Laboratory of Ocean Circulation and Waves, Institute of Oceanology, and Center for Ocean Mega-Science, Chinese Academy of Sciences, Qingdao 266071, China

² Laboratory for Ocean and Climate Dynamics, Pilot National Laboratory for Marine Science and Technology, Qingdao 266237, China

³ Center for Excellence in Quaternary Science and Global Change, Chinese Academy of Sciences, Xi'an 710061, China

⁴ University of Chinese Academy of Sciences, Beijing 100049, China

⁵ LASG, Institute of Atmospheric Physics, Chinese Academy of Sciences, Beijing 100049, China

⁶ First Institute of Oceanography, Ministry of Natural Resources, Qingdao 266061, China

⁷ Laboratory for Regional Oceanography and Numerical Modeling, Pilot National Laboratory for Marine Science and Technology, Qingdao 266237, China

⁸ Key Laboratory of Marine Science and Numerical Modeling (MASNUM), Ministry of Natural Resources, Qingdao 266061, China

⁹ National Engineering Laboratory for Integrated Aero-Space-Ground-Ocean Big Data Application Technology, Qingdao 266061, China

¹⁰ State Key Laboratory of Severe Weather, Chinese Academy of Meteorological Sciences, Beijing 100081, China

¹¹ Laboratory for Climate Studies and CMA-NJU Joint Laboratory for Climate Prediction Studies, National Climate Center, China Meteorological Administration, Beijing 100081, China

¹² Environmental Science and Engineering, University of Northern British Columbia, British Columbia V2N 4Z9, Canada

¹³ State Key Laboratory of Satellite Ocean Environment Dynamics, Second Institute of Oceanography, Ministry of Natural Resources, Hangzhou 310012, China

¹⁴ Key Laboratory of Meteorological Disaster, Ministry of Education (KLME), and Collaborative Innovation Center on Forecast and Evaluation of Meteorological Disasters (CIC-FEMD), Nanjing University of Information Science and Technology, Nanjing 210044, China

¹⁵ Beijing Climate Center, China Meteorological Administration, Beijing 100081, China

用于厄尔尼诺-南方涛动(ENSO)研究的海气耦合模式综述: 中间型和混合型模式*

张荣华^{1,2}

(1. 南京信息工程大学海洋科学学院 江苏南京 210044; 2. 崂山实验室 山东青岛 266237)

摘要 厄尔尼诺-南方涛动(El Niño-Southern Oscillation, ENSO)是地球气候系统中最强的年际变率信号,起源于热带太平洋海气相互作用过程,并对全球的天气和气候等产生显著的影响。过去几十年来,广泛、深入而细致的海气相互作用研究致力于发展和改进海气耦合模式以用于 ENSO 模拟和预测,各种类型的海气耦合模式应运而生。经过半个多世纪的努力,ENSO 数值模式及其应用已经取得了巨大进展,包括已发展了一些高度理想化的概念(concept)模型来解释 ENSO 准周期性循环(包括正负反馈机制等);同时也已发展了几类复杂程度不同的海气耦合模式并用于对 ENSO 的真实模拟和实时预测等研究,尤其是已能提前 6 个月或更长时间对 ENSO 事件的发生和发展等进行有效的实时预测。其中最为复杂的模式是基于原始方程组的大气环流模式(Atmospheric General Circulation Models, AGCMs)与海洋环流模式(Oceanic General Circulation Models, OGCMs)等所组成的环流型耦合模式(Coupled General Circulation Models, CGCMs),这类模式变量取为完全变量的形式(如总的海表温度场,其可以分解为气候态部分和年际异常部分),还考虑了尽可能详尽的物理过程及其参数化方案。中间型耦合模式(Intermediate Coupled Models, ICMs)是一类介于高度理想化概念模型与复杂的环流型耦合模式之间的简化模式,其对应的控制方程组采用距平形式,直接取大气和海洋年际异常场作为预报变量(如海表温度年际异常),而相应的气候平均态部分则由对应的观测资料来给定;大气与海洋模式间的耦合采用异常耦合(anomaly coupling)。混合型耦合模式(Hybrid Coupled Models, HCMs)是另一类简化的海气耦合模式,其中海洋或大气模式有一个分量模式采用了简化的距平类模式(类似于 ICMs),而另一个分量模式则采用环流型模式(General Circulation Models, GCMs);如可采用统计的大气风应力年际异常模式与 OGCM 间的耦合而构建一种 HCM_{OGCM},也可采用简化的海洋距平类模式(如 ICM 中的海洋分量模式)与 AGCM 间的耦合而构建另一种 HCM^{AGCM}。历史上,ICMs、HCMs 和 CGCMs 等这几类耦合模式都在 ENSO 理论体系的发展、数值模拟和实时预测等方面都起到了重要作用。本文主要回顾作者与合作者所研发的 ICMs 和 HCMs 的构建、特点和应用例子等。

关键词 厄尔尼诺-南方涛动(ENSO); 海气相互作用; 中间型耦合模式; 混合型耦合模式; ENSO 模拟性能

中图分类号 P733.1

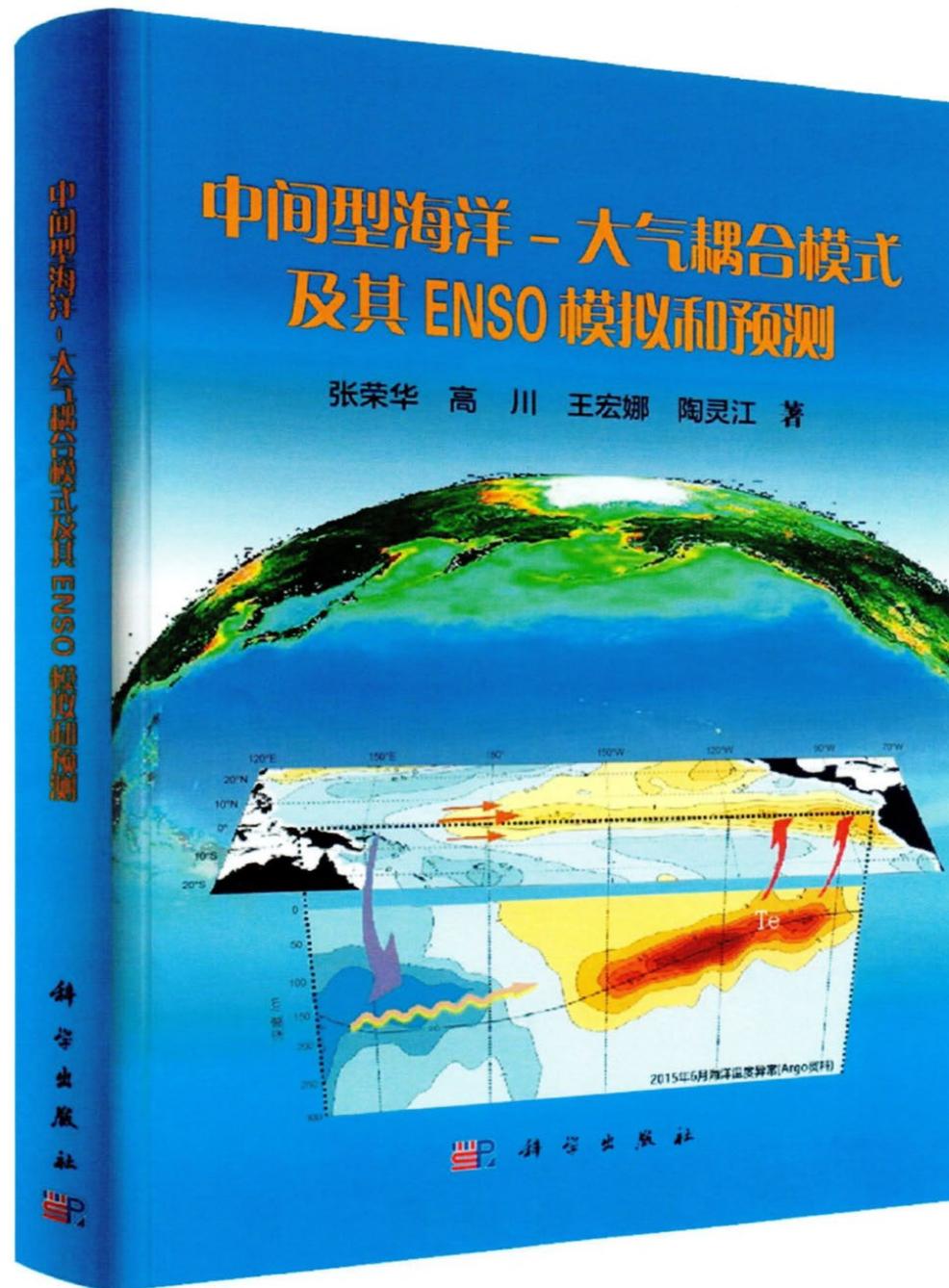
doi: 10.11693/hyhz20230600120

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张荣华 高川 王宏娜 陶灵江：

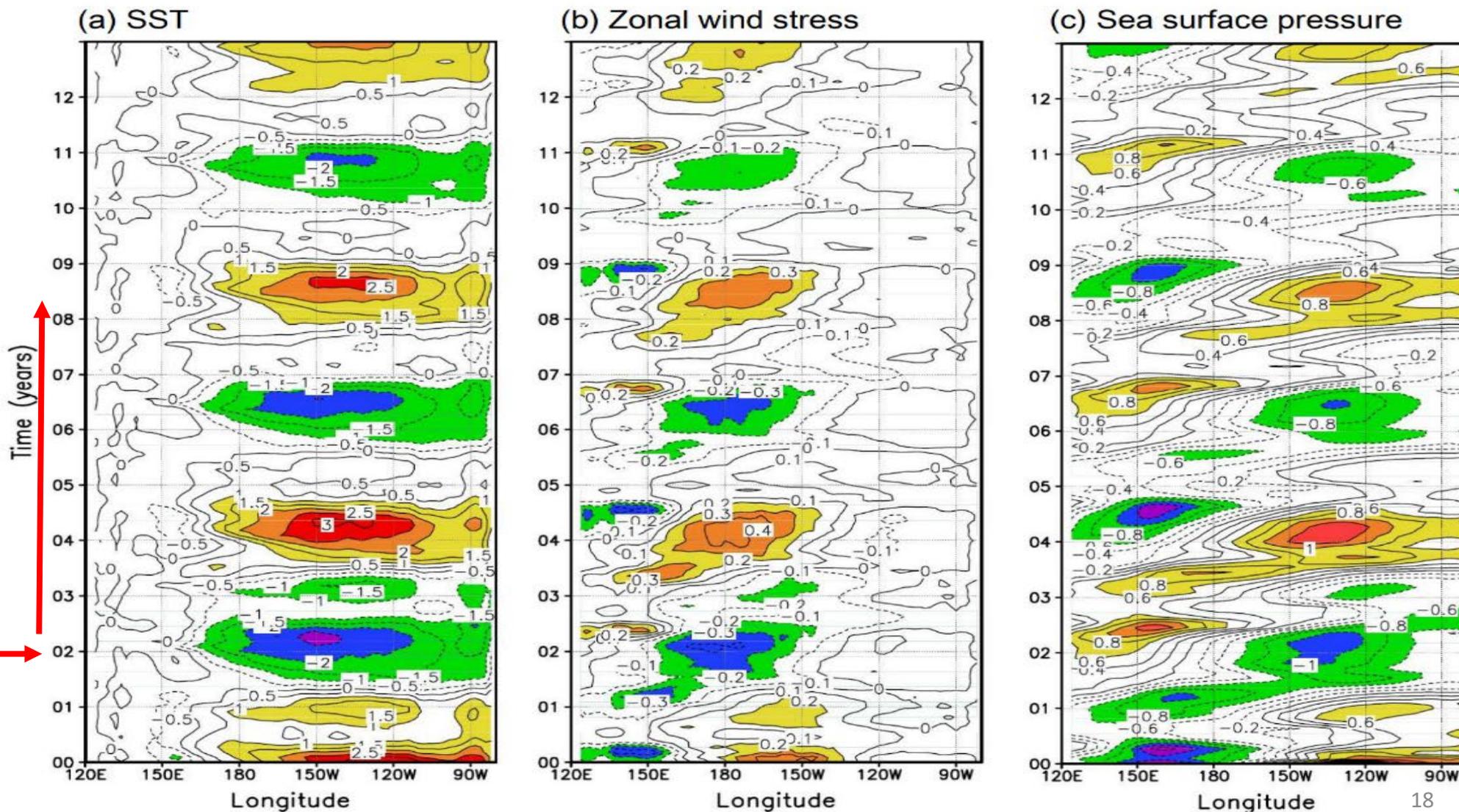
《中间型海洋-大气耦合模式
及其 ENSO 模拟和预测》

2021，科学出版社；
入选中国海洋学会2022年度
海洋优秀科技图书入库名单



海气耦合模式模拟得到的沿赤道的时空演变：

Anomalies along the equator

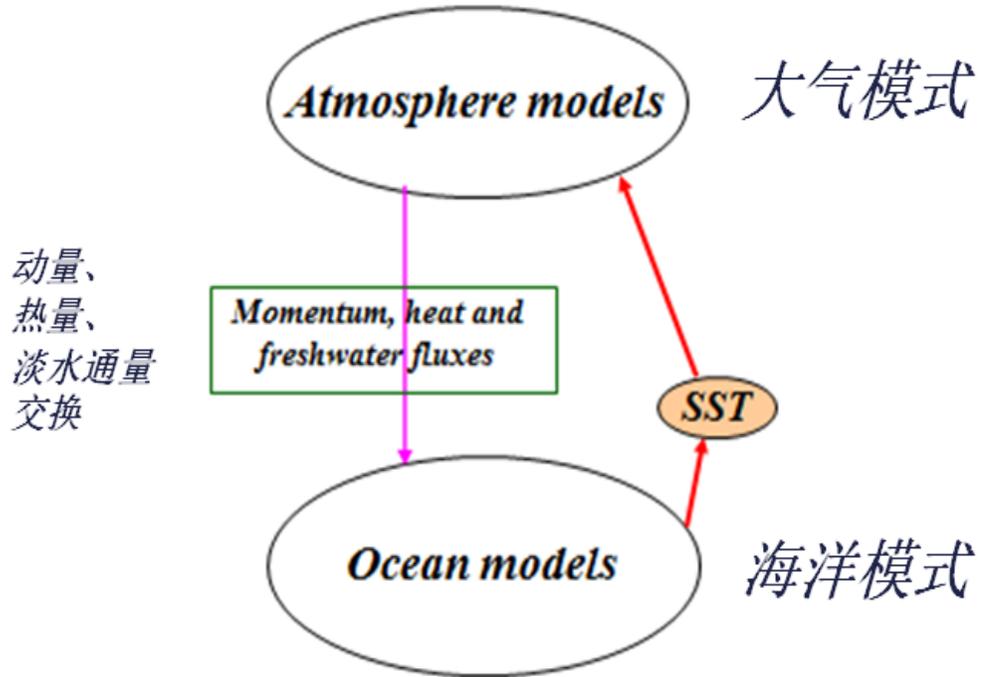


作为初始场
进行预测

基于动力过程的 ENSO 模式

海气耦合模式

Coupled ocean-atmosphere models
(ICMs, HCMs and CGCMs)



- 概念模式
- 中等型耦合模式 (ICMs)
- 混合型耦合模式 (HCMs)
- 耦合环流模式 (CGCMs)

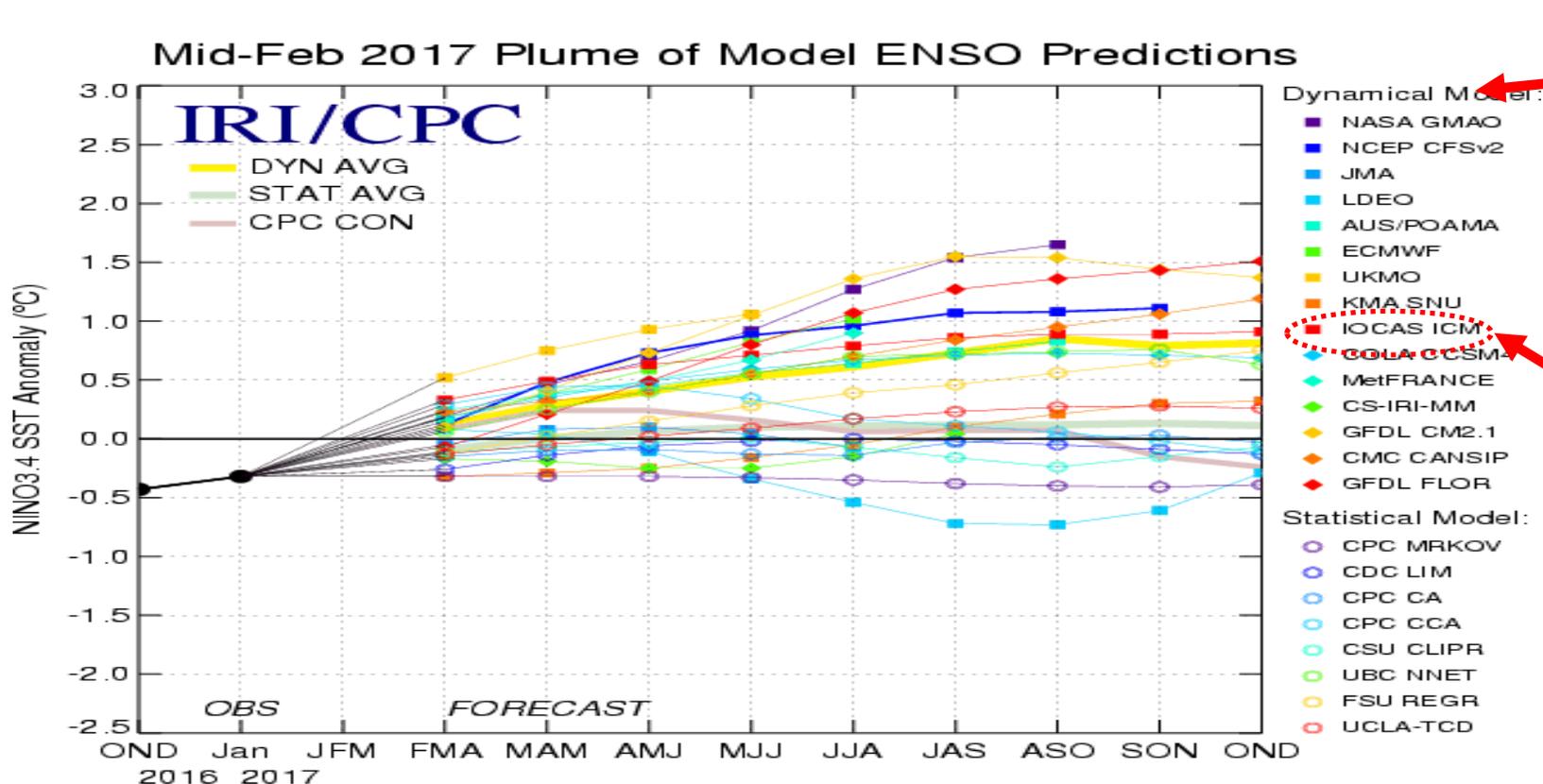


模拟对模式的强烈依赖性！

ENSO模拟和实时预测

建立了中科院海洋所海气耦合模式 (IOCAS ICM) ， 并进行 ENSO 实时预测

敬请关注： [IOCAS ICM online at: http://iri.columbia.edu](http://iri.columbia.edu)



世界上20多个耦合模式的 ENSO 预报结果

以我国国内单位冠名的海气耦合模式为国际学术界提供 ENSO 实时预报结果

预测瓶颈！ 如何提高 ENSO 的准确预测精度？

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基于物理的 ENSO 模式及预测

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基于 Transformer 的 ENSO模型

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物理模式和数据驱动模型的融合

物理模式中引入深度学习 (DL) 方法

DL模型中引入物理模式 (约束)

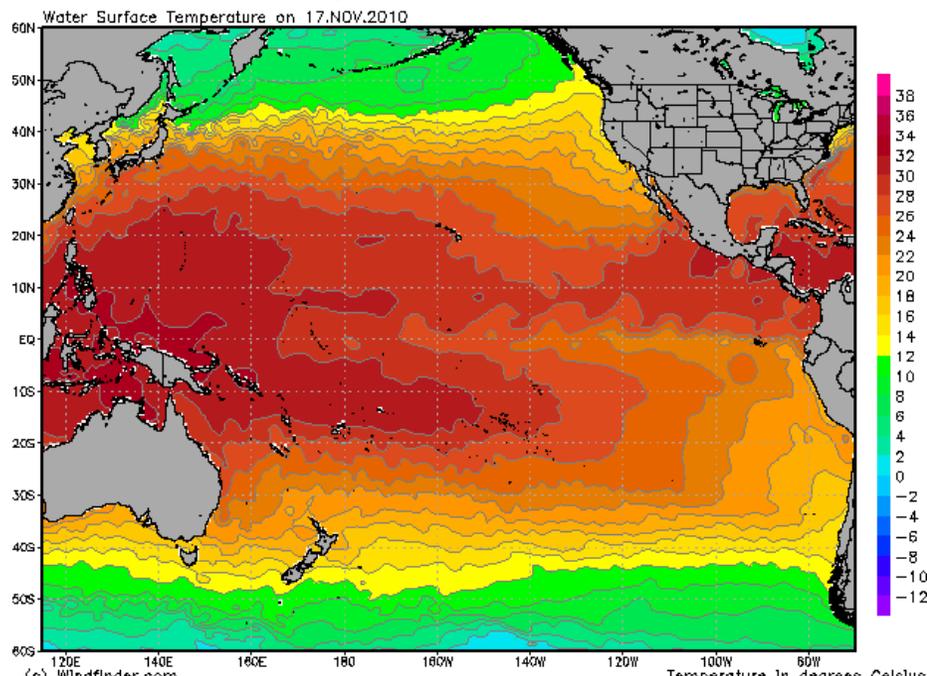
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总结与讨论

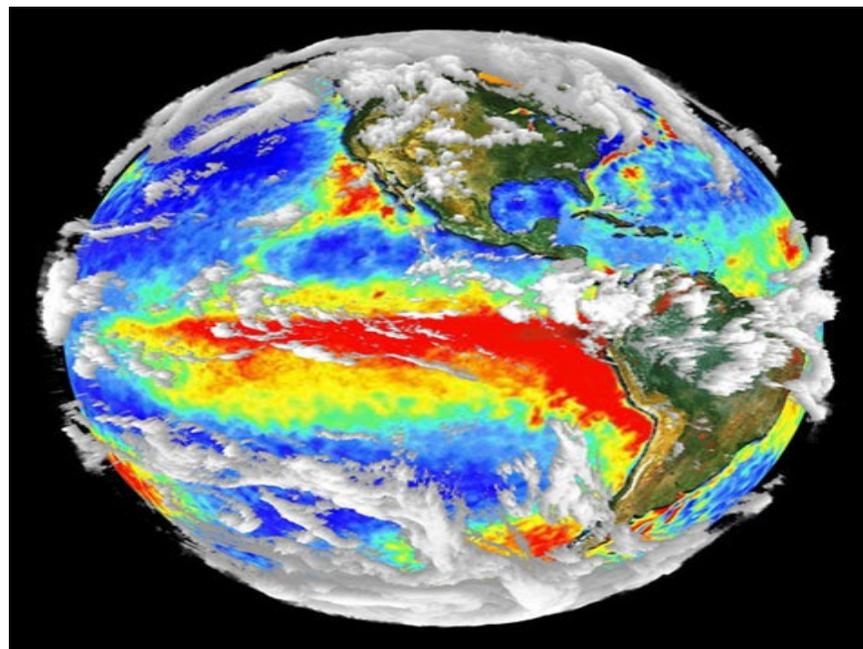
一个基于 **Transformer** 架构的海洋-大气耦合模式 及其在 **ENSO** 研究中的应用

张荣华 周路 高川
南京信息工程大学海洋科学学院等

太平洋海表温度 (SST) 平均气候态分布



1997年12月SST年际异常: El Nino



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2023-24年实时预测

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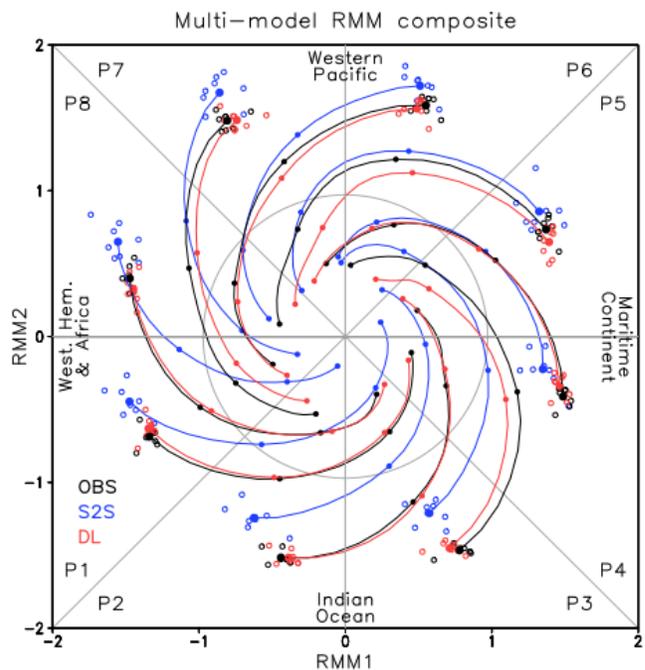
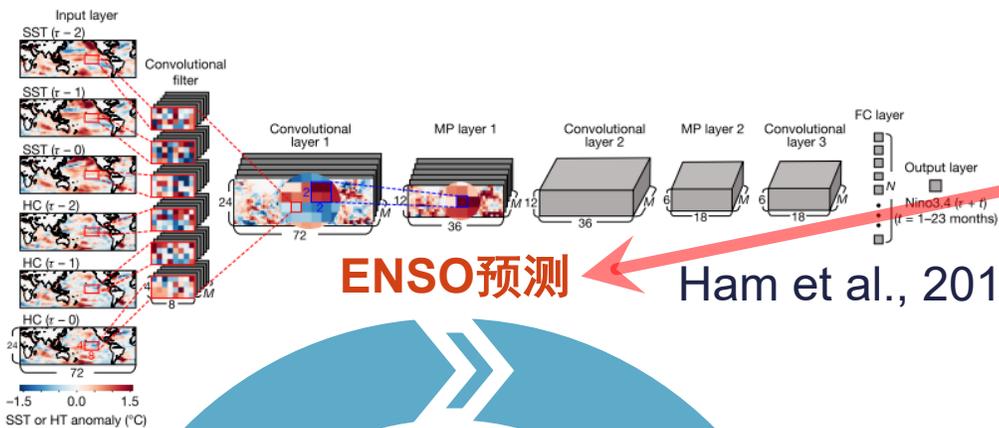
敏感性试验：海气动力学及可解释性

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总结与讨论

1. 研究背景

人工智能(AI)技术已成功应用于天气、气候领域



Kim et al., 2021

模式误差修正

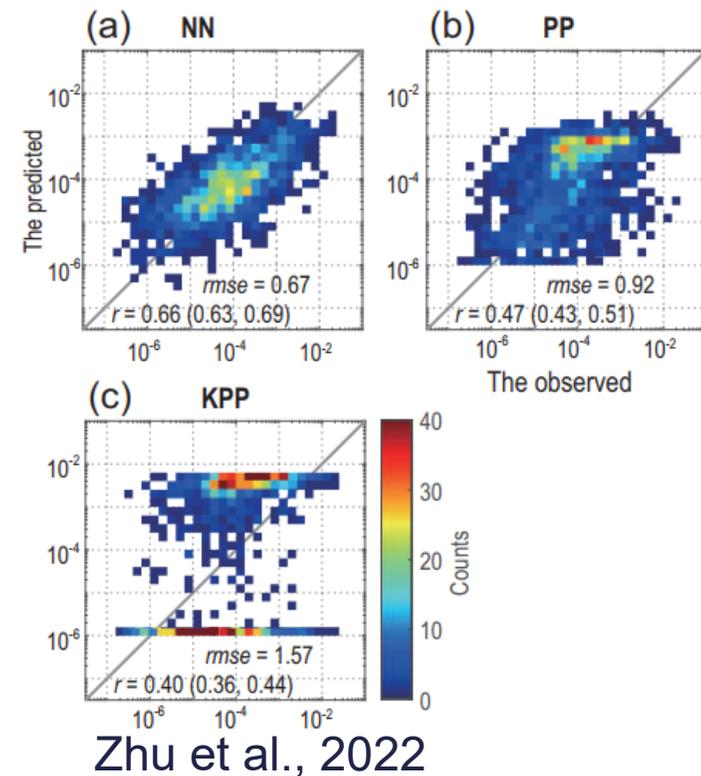


构建模式参数化方案

短时降水预报



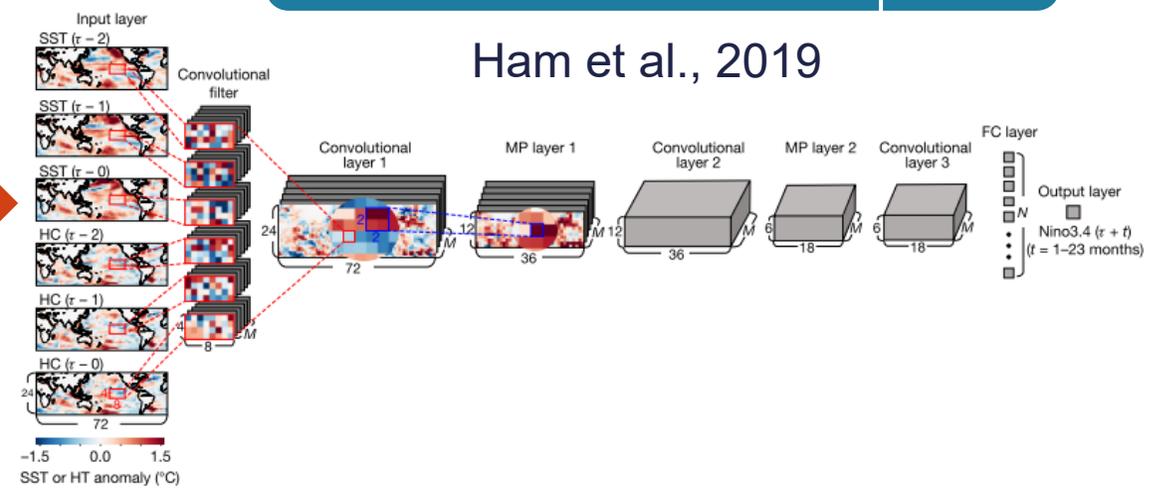
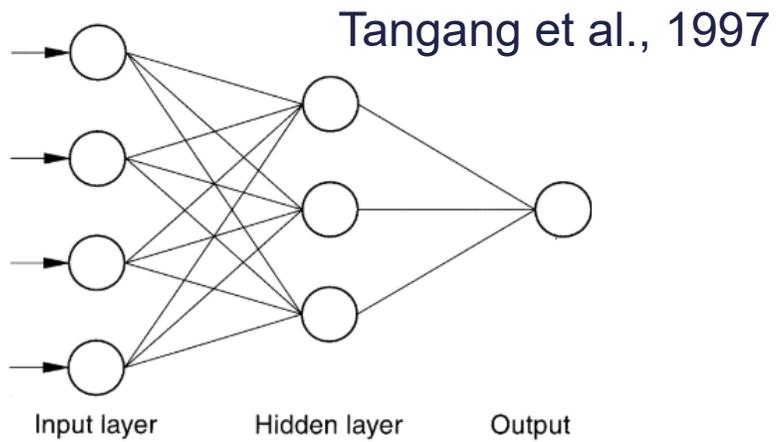
Ravuri et al., 2021



1. 研究背景：基于 AI 的 ENSO 预测研究正从 **单点、单变量向多变量、三维场预测的跨越**

Wind stress PCs+ Niño3.4 index → Niño3.4 index **点→点**

SST+HC → Niño3.4 index **面→点**



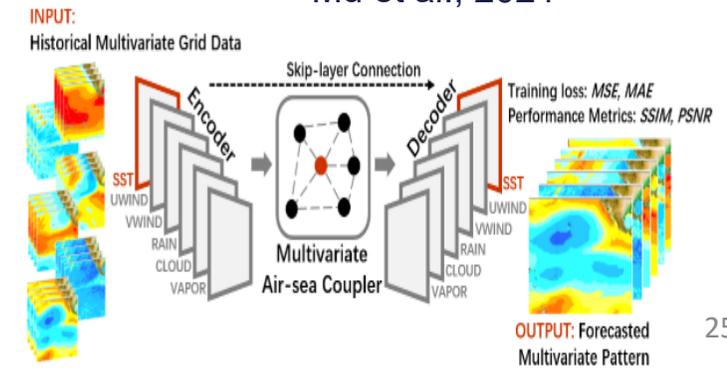
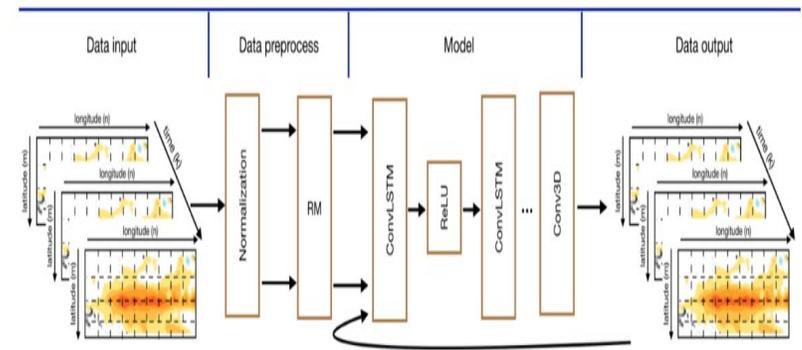
SST → SST **面→面**

多变量 → 多变量 **体→体**

Air-sea Coupling

Mu et al., 2019

Mu et al., 2021

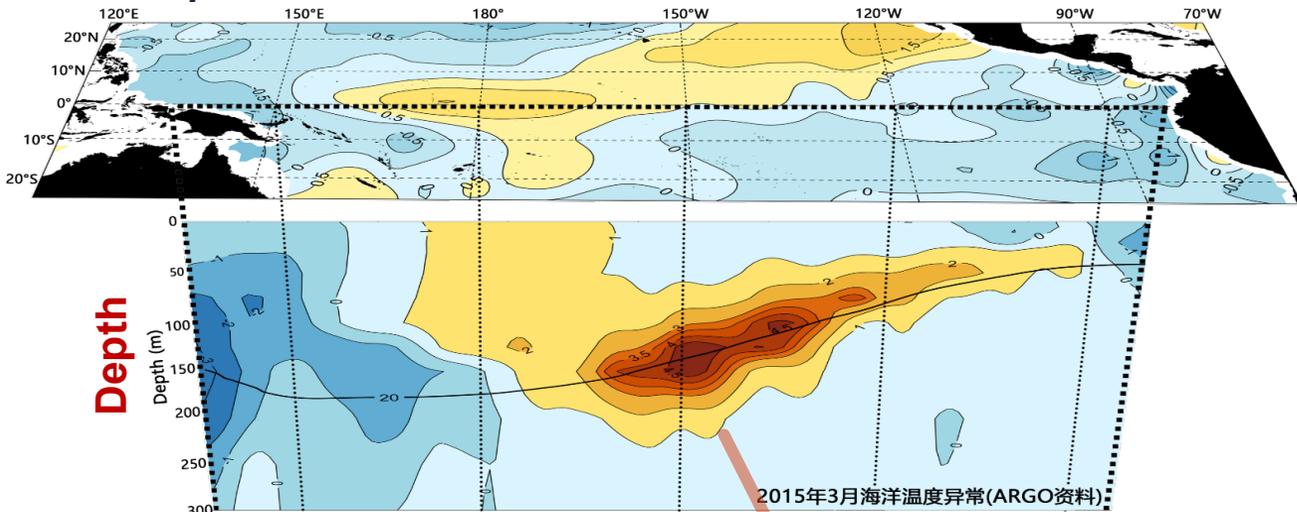


1. 研究背景

ENSO 预测的物理基础：多变量三维场时空演变和相互作用

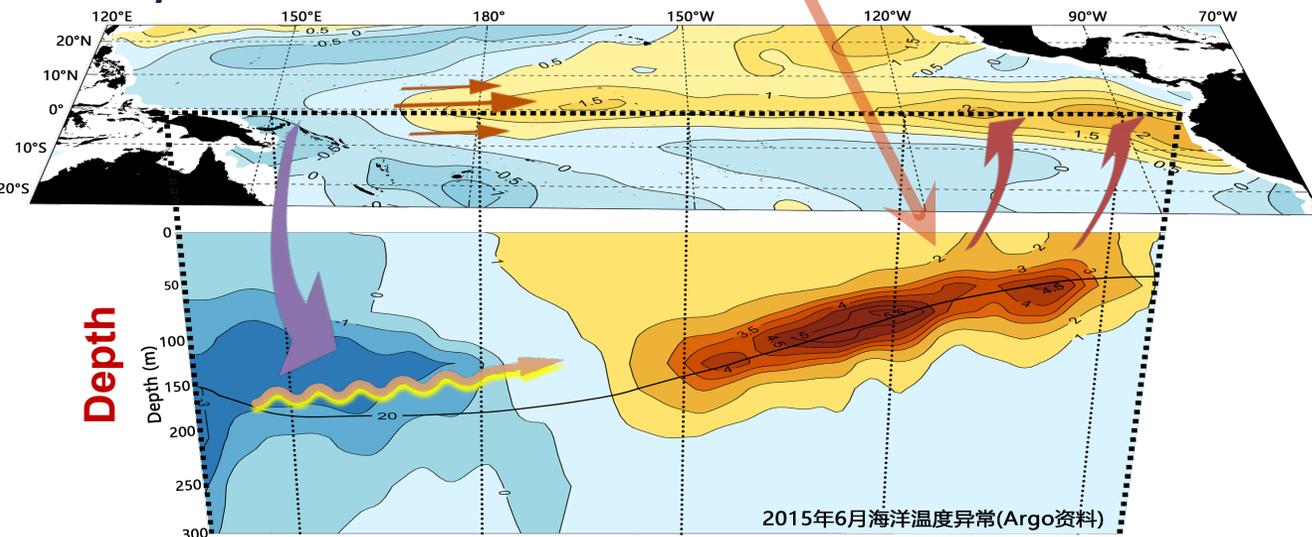
时空演变和海气相互作用

March, 2015



2015年3月海洋温度异常(ARGO资料)

June, 2015



2015年6月海洋温度异常(Argo资料)

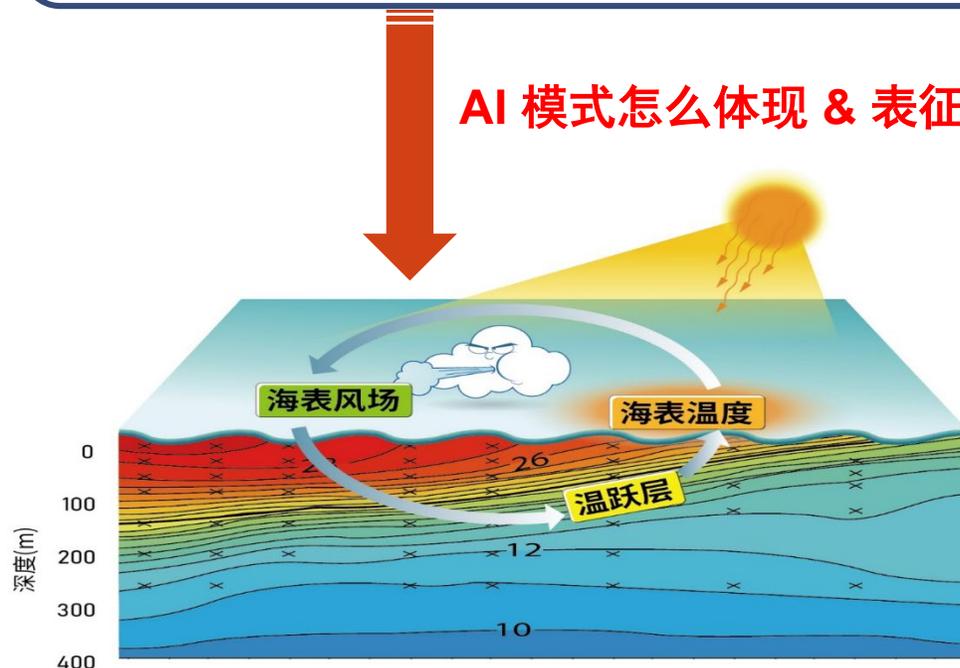
时间尺度：季节到年际

空间尺度：整个热带太平洋；海气异常协同变化

ENSO 有明确的过程和机制：次表层异常信号显现出传播性和持续性；激发远程响应、反馈和海气相互作用；使得海气异常产生后可在季节到年际时间尺度上得以维持。这种次表层中年际尺度的“记忆”能力为 ENSO 预测提供了物理基础

多变量相互作用提供了 ENSO 可预测性

AI 模式怎么体现 & 表征 ?



1. 研究背景

数据驱动的多变量三维场耦合及时空预测模型

高要求

- 更真实地表征多变量场间动力学关系
- 保证物理过程的完备性与预测结果的可信度
- 具有更强大的理论验证与知识挖掘潜力
- 拥有更准确、泛化的业务化应用前景

挑战性

数据层面：观测数据时间短，空间分布不均，质量控制参差不齐

算法层面：高维时空建模预测对传统卷积(CNN)、循环(RNN)神经网络颇具挑战

算力层面：训练高维时空预测模型所需计算资源巨大，经济成本高

应用层面：泛化能力弱，推广拓展能力差

物理层面：表征能力弱，可解释性差 ?

模式数据预训练+
观测数据迁移学习

开发兼顾时间依赖与空间
遥相关分析能力的AI模型

构建空间分辨率可变、计算
并行化、计算成本可控
的地质预测模型

开发AI+物理约束的智能
通用气候系统模型

2. 研究内容与目标：利用 AI 开展海洋- 大气年际异常多变量三维场预测研究

基于物理过程的动力模式对 ENSO 的实时预测仍存在较大误差与不确定性，近年来，人工智能（AI）技术已在天气预报和气候预测等领域取得了重大进展（如数据驱动深度学习模型已成为热带太平洋海表温度（SST）预测的重要方法）。但目前这些数据驱动的神经网络模型对海洋动力与热力状态等的表征、模拟和预测应用相对较少，如大多是对单点时间序列或单变量场进行预测的，难以表征多变量时空演变及其内在的关联，其结果的应用性非常有限。当前用 AI 对海洋多变量三维（3D）场时空演变的表征和跨年度 ENSO 预测仍存在着很大的挑战。

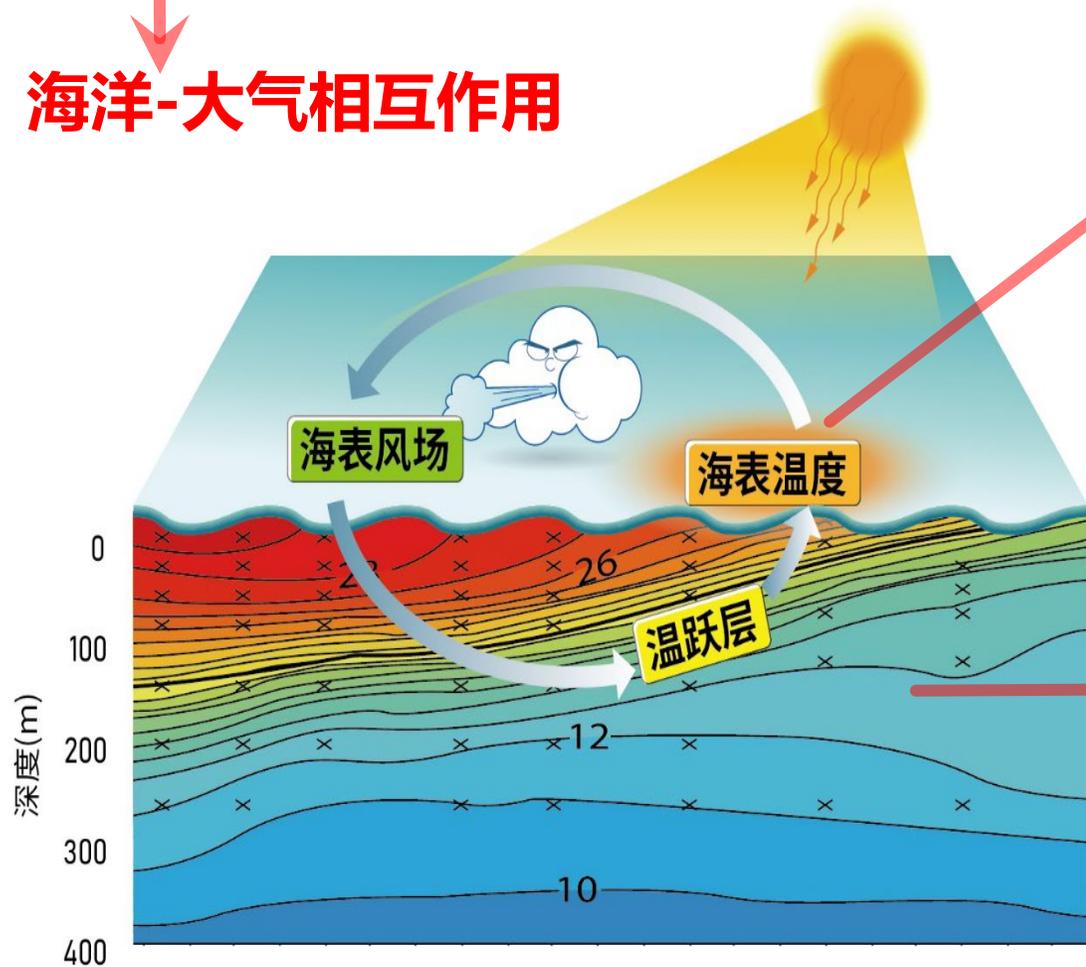


利用目前 AI 中最为先进的 Transformer 构架，本研究旨在构建数据驱动的热带太平洋海气系统多变量三维场预测模型，并实现对 ENSO 现象相关的三维海温和风场的跨年度准确预测。实现从单一变量、单点时间序列的预测到海气系统多变量、三维立体场预测的跨越，为海气耦合模拟和预测提供了一个新的有效工具。

2. 研究内容与目标

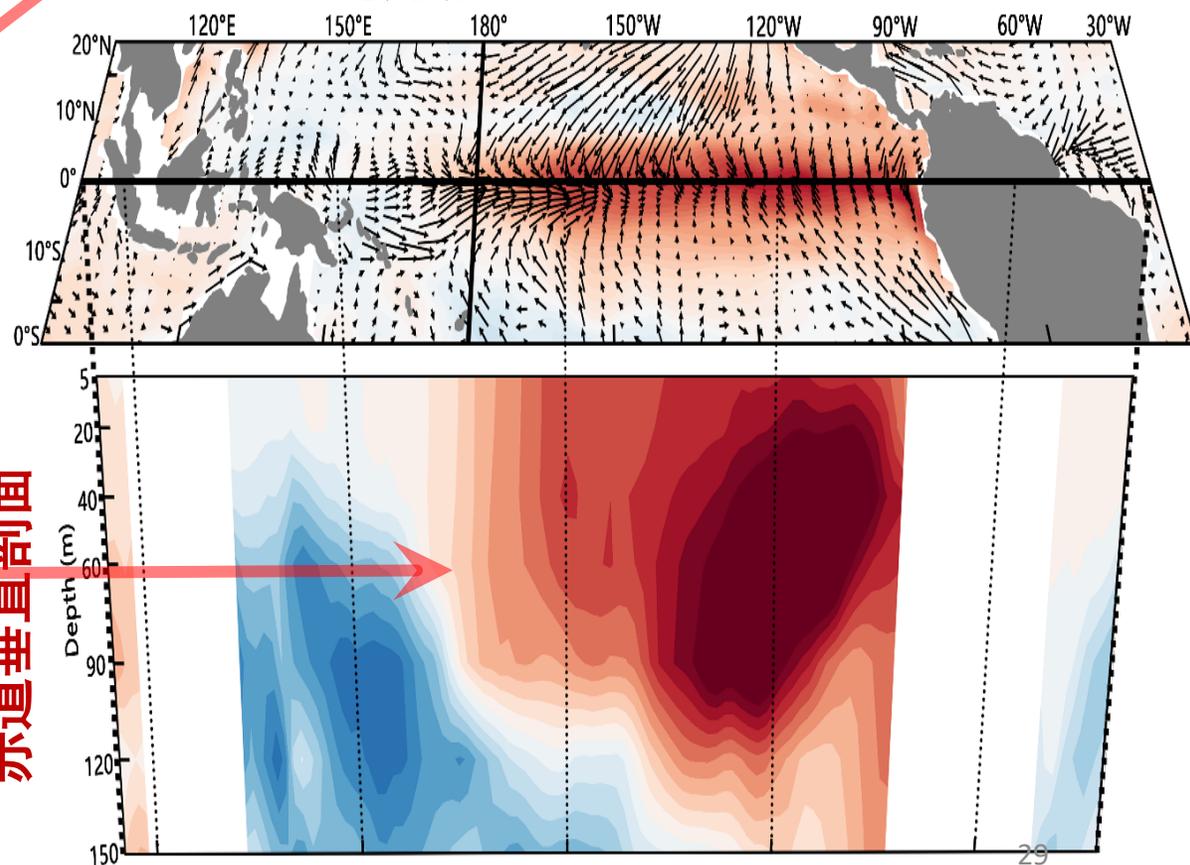
构建基于**自注意力机制**的多变量三维场时空预测模型，充分发挥自注意力机制在**空间非局地信息分析及长时间序列分析**方面优势。

海洋-大气相互作用



风场和海洋三维温度场等多变量

Dec 2015 观测场



3. 数据与模型

研究目的与方法

Transformer-based model:

本研究根据气候数据**强时间依赖性**和**空间相关性**特点，在 Transformer 架构基础上通过构建特殊的**时空注意力模块**强化了模型对数据时空特征的分析能力，率先成功构建了由数据驱动的热带太平洋海气系统**多变量三维场预测模型**，并实现了对厄尔尼诺与南方涛动(ENSO)现象相关的三维海温和风应力场的跨年度准确预测。

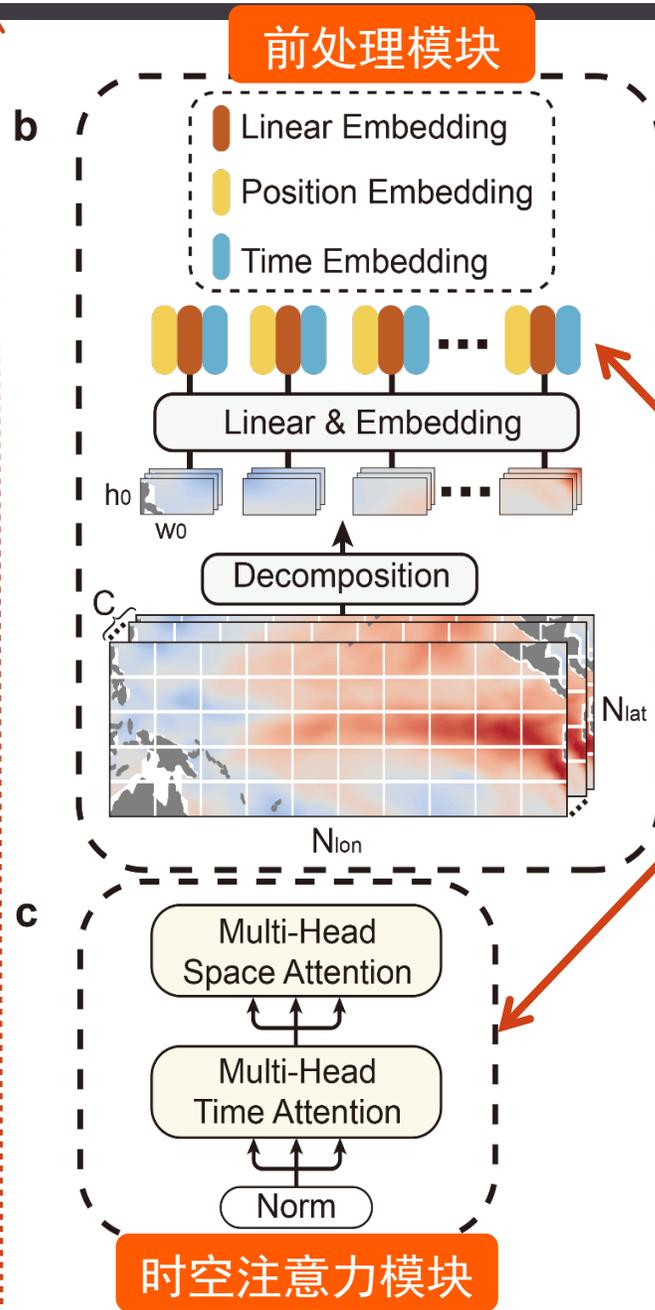
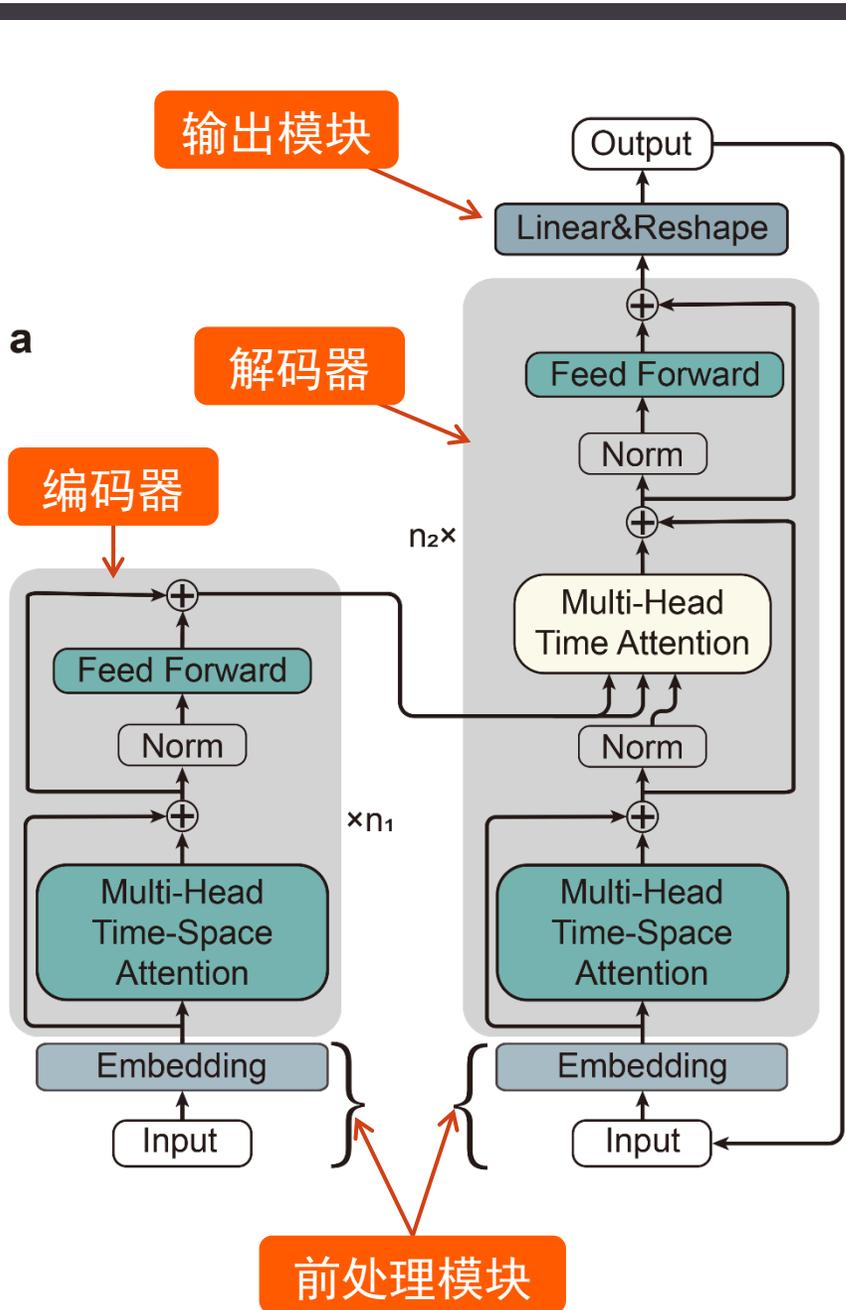
研究区域与数据

研究区域及空间分辨率	92°E-330°E, 20°S-20°N	5°N/S以外: 2°*1° 5°N/S以内: 2°*0.5°
变量	5, 20, 40, 60, 90, 120, 150m海温场和经向、纬向风应力场	

数据集	数据来源	时间
训练集	CMIP6 historical月平均数据	1850-2014
验证集	SODA和ORAS5月平均再分析数据	1871-1979
测试集	GODAS再分析月平均数据	1980-2021

3. 数据与模型

开展基于神经网络模型 (3D-Geoformer) 的多变量三维场时空异常场预测



✓模型整体为编码器-解码器架构 (Encoder-Decoder):

前者对输入变量进行时空注意力计算并生成记忆矩阵, 后者通过解构已有预测场与编码器记忆矩阵的相关关系生成下一时间步预测场。

✓时间和空间位置编码:

克服注意力计算无法区分序列位置信息的缺陷, 模型可以更好理解不同时刻不同位置的变量信息。

✓多头时空注意力计算:

将输入向量分为多段(或多头: multi-head), 每个头分别执行独立的注意力计算, 以增强模型对序列不同位置信息的关注能力。

✓时间依赖与空间遥相关性的学习:

Transformer类似于图建模方法, 可以通过注意力计算一次性获取所有时空格点变量间关系。

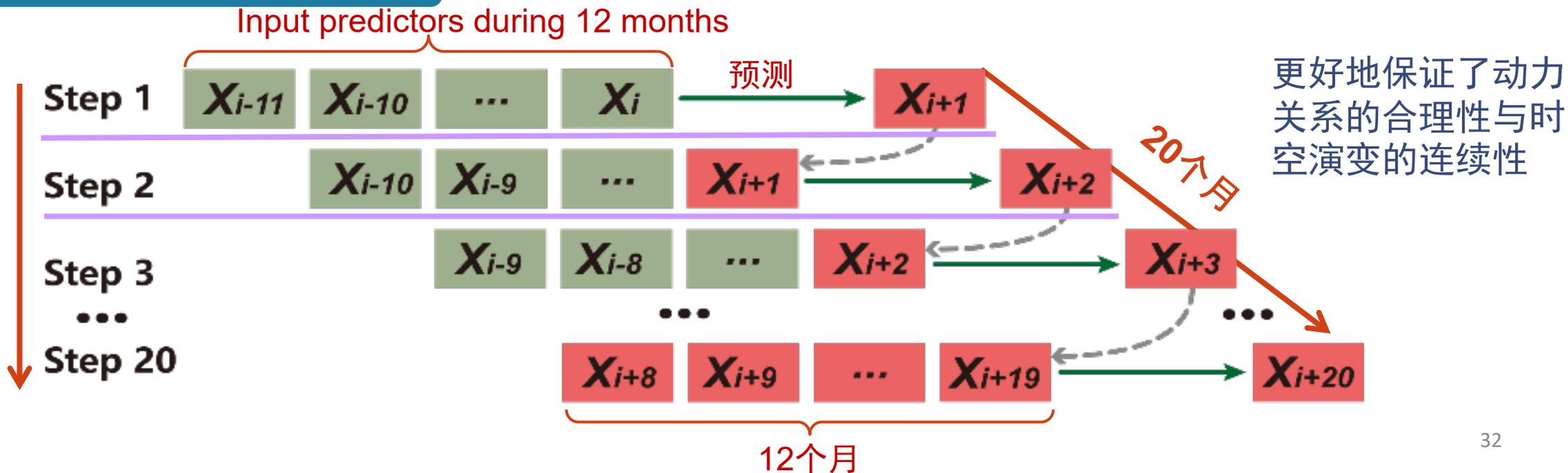
3. 数据与模型

损失函数及优化

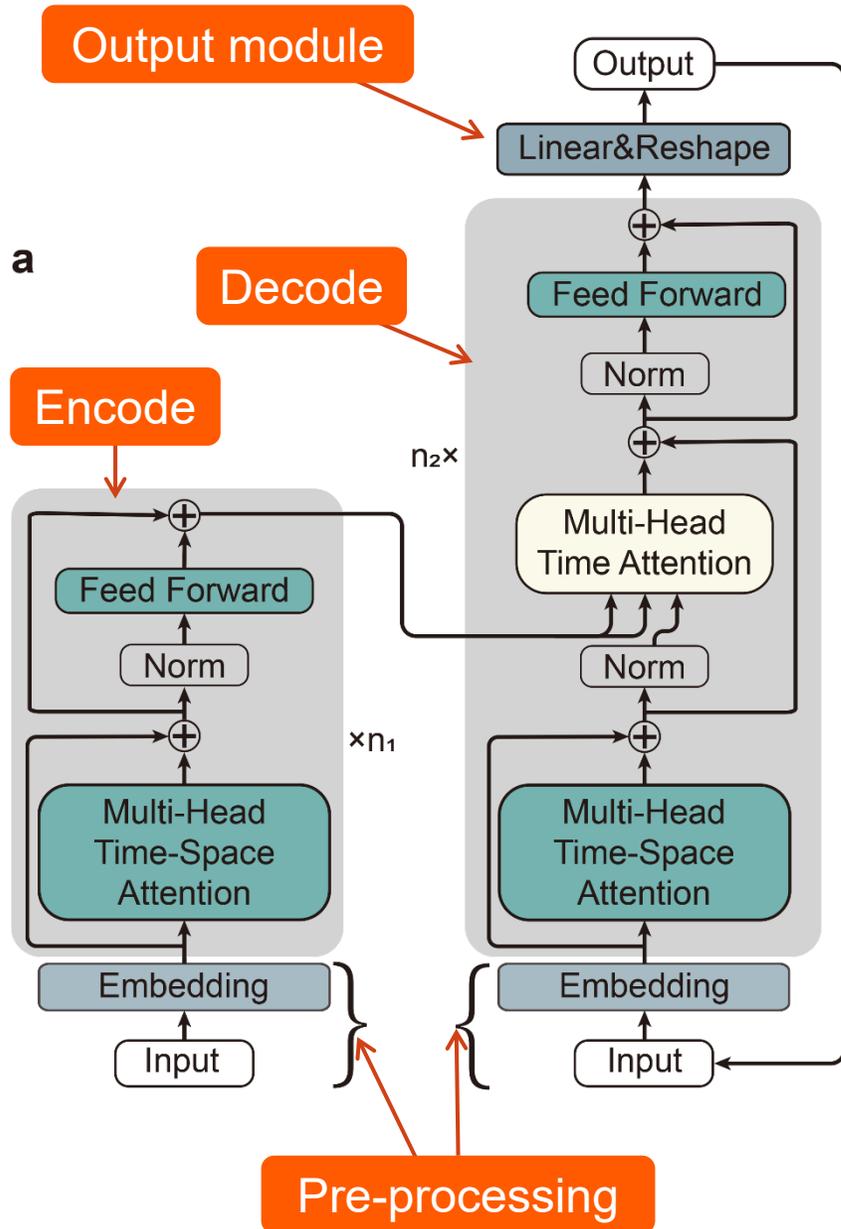
$$Loss = \frac{1}{T_{out}} \sum_{t=1}^{T_{out}} \left(\underbrace{\sqrt{\frac{1}{N_{lat} \times N_{lon} \times C} \sum_{i=1}^{N_{lon}} \sum_{j=1}^{N_{lat}} \sum_{k=1}^C (X_{t,k,j,i}^{out} - X_{t,k,j,i}^{tg})^2}}_{\text{多变量场RMSE}} + \underbrace{\sqrt{(Ni\~{n}o34_t^{out} - Ni\~{n}o34_t^{tg})^2}}_{\text{Ni\~{n}o3.4指数RMSE}} \right)$$

- 模型针对Niño3.4区域SST场进行了重点优化
- 模型采用Adam 优化器
- 采用 warming up学习率调整策略
- 采用早停(early stop)机制避免模型过拟合

模型预测：逐月滚动预测方法



3. Data & model: A attention-enhanced transformer model for 3D field predictions (3D-Geoformer)



For details: **coding**

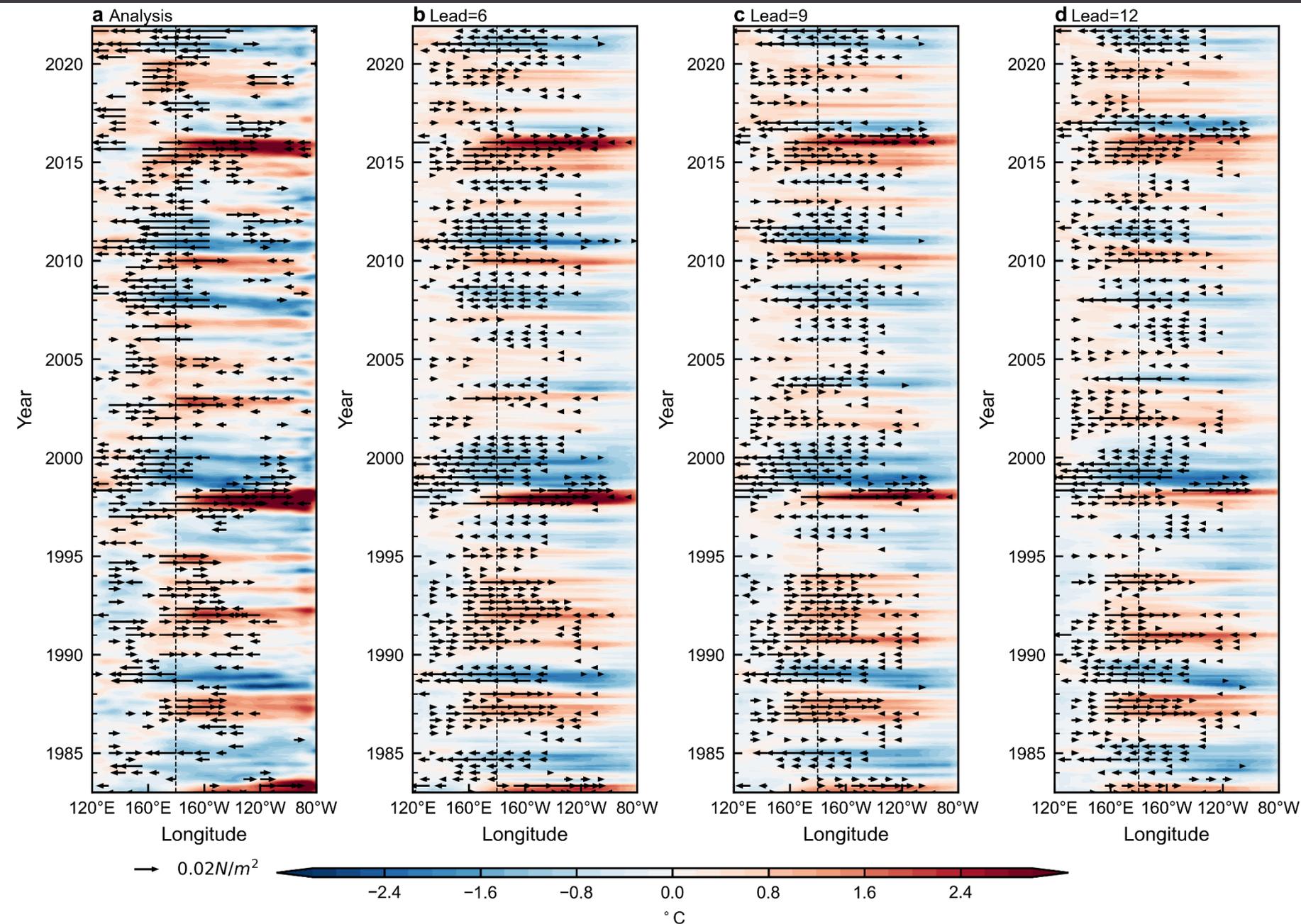
Science Advances

A self-attention-based neural network for three-dimensional multivariate modeling and its skillful ENSO predictions

Lu Zhou, Rong-Hua Zhang

Related paper: Zhou, L., and R.-H. Zhang, 2023: A self-attention based neural network for three-dimensional multivariate modeling and its skillful ENSO predictions. *Science Advances*, 9, eadf2827, <https://doi.org/10.1126/sciadv.adf2827>.

4.1 模型预测技巧评估: 多变量场预测

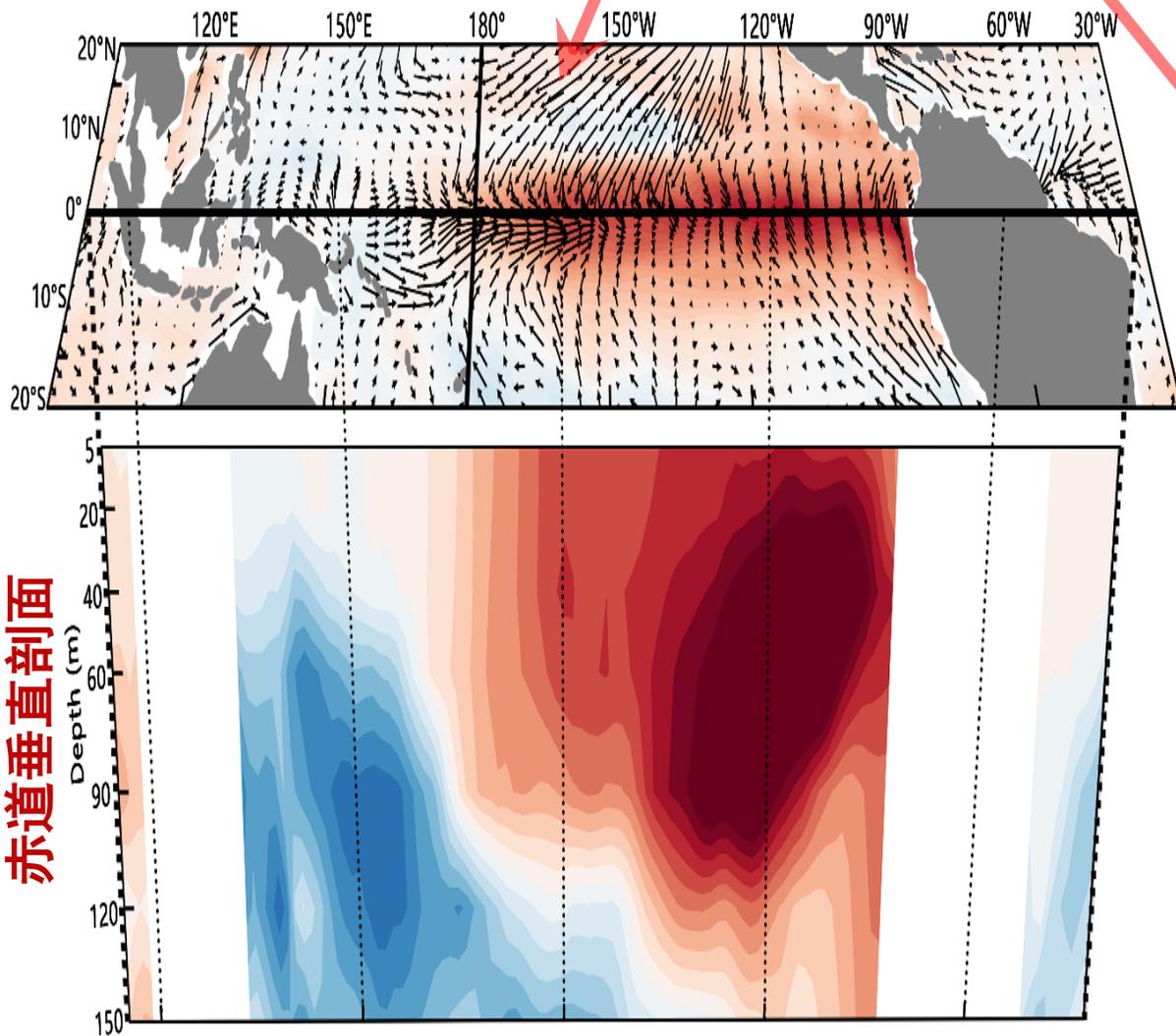


GODAS再分析及模式预测得到的赤道SST及纬向风应力时间演变

- 该3D-Geoformer模型可以准确学习风场与海温场间的耦合动力学关系，如El Niño期间中西太平洋西风异常和La Niña期间的东风异常等。
- 随着提前预报时间的增长，预测得到的变量振幅和位相偏差较小。

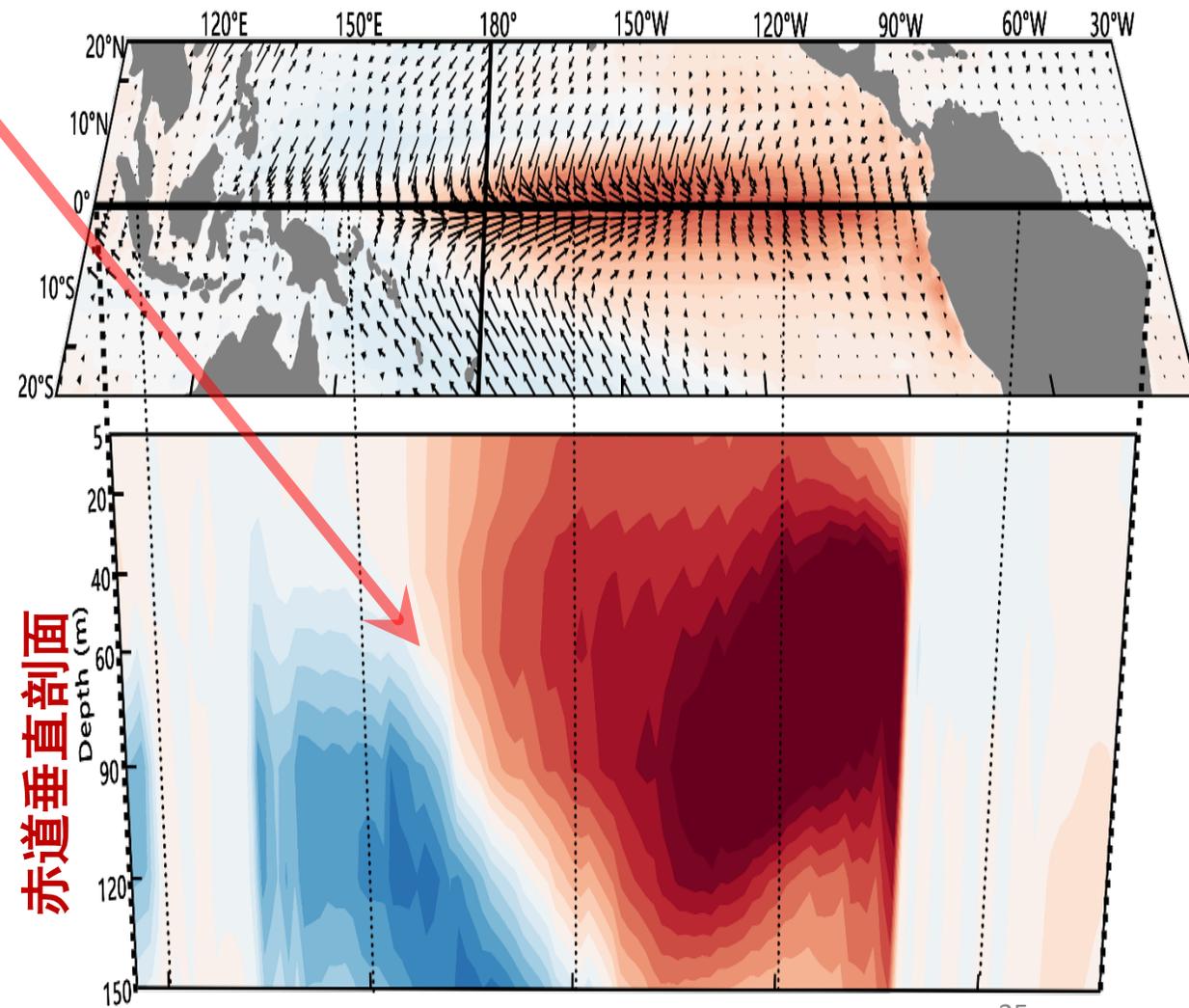
风场和海洋三维温度场等多变量预测

Dec 2015 观测场



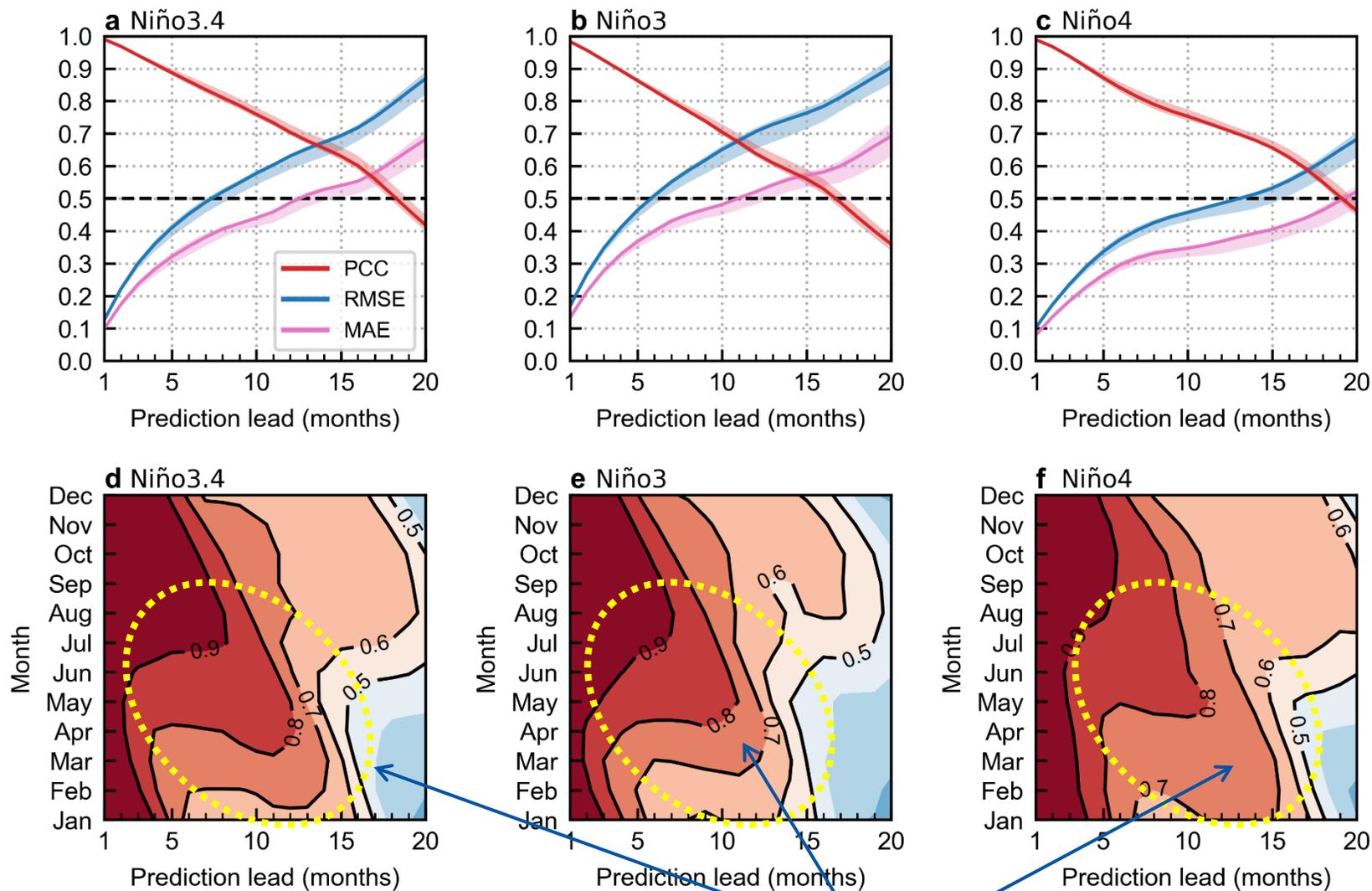
赤道垂直剖面

Dec 2015 提前9个月预测场



赤道垂直剖面

4.2 模型预测技巧评估：Niño指数的预测



•该3D-Geoformer的ENSO预测水平可达到先进神经网络模式水平，并明显优于动力模式。

•提前**18个月**对Niño3.4海温异常进行有效预测

•提前**16个月**对Niño3海温异常进行有效预测

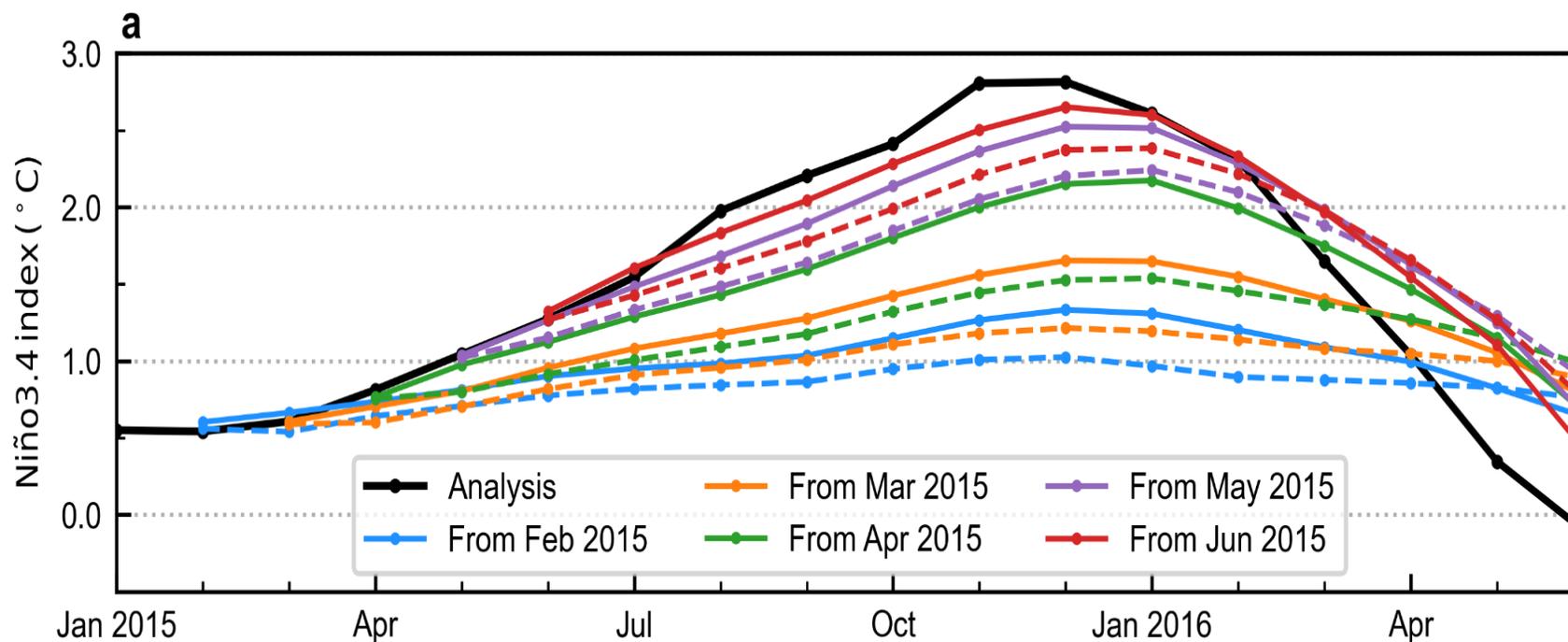
•提前**19个月**对Niño4海温异常进行有效预测

•对ENSO的高水平预测的实现离不开损失函数中对Niño3.4区域海温的重点优化

• 3D-Geoformer模型对Niño指数的预测技巧及其季节变化

春季预报障碍 (SPB)
问题得到有效改善

4.3 模型预测技巧评估: 2015-16年超强El Niño预测个例分析



2015-16年超强El Niño事件中Nino3.4区海温异常演变。黑线为再分析结果；彩色线为3D-Geoformer模型从不同月份开始的预测值：

实线是模型输入场包含海温异常和风应力的结果，虚线为去除热带太平洋风应力影响后的结果(只有海温的影响)。

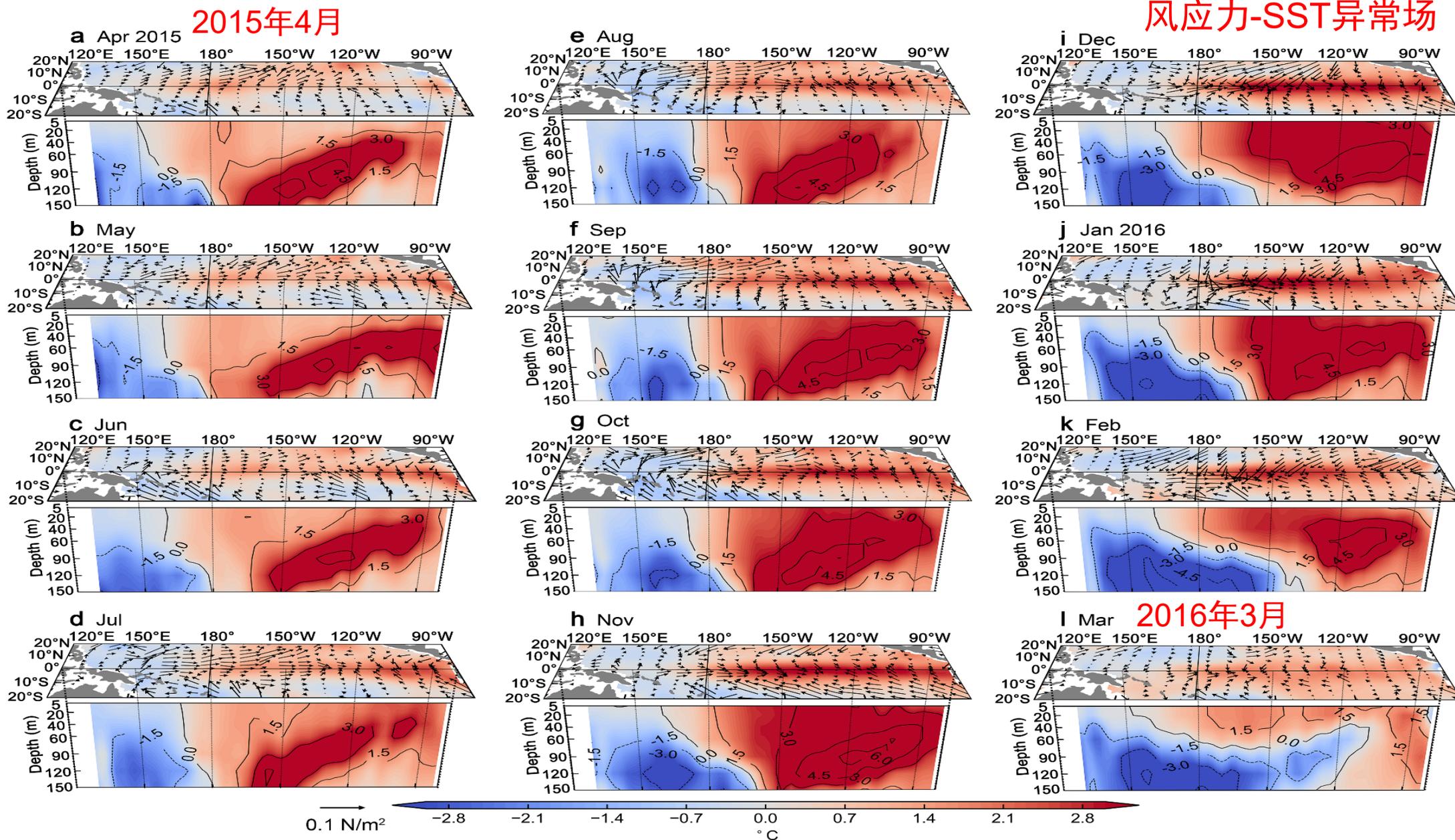
- 以2015-16年超强El Niño为例，检验该 3D-Geoformer模型对极端ENSO事件的预测能力：从 2015年4月开始该模型即可准确预测此事件的发展以及成熟期海温异常的强度。
- 通过敏感性试验探究关键海气变量（如风应力）在此次事件演变中的作用。
- 例如，去除热带太平洋风应力的影响后模型对成熟期海温异常的强度预测明显偏小，体现了在数据驱动模型中正确表征海气耦合关系的重要性。

4.3 模型预测技巧评估: 2015-16年超强El Niño个例分析 (GODAS 再分析)

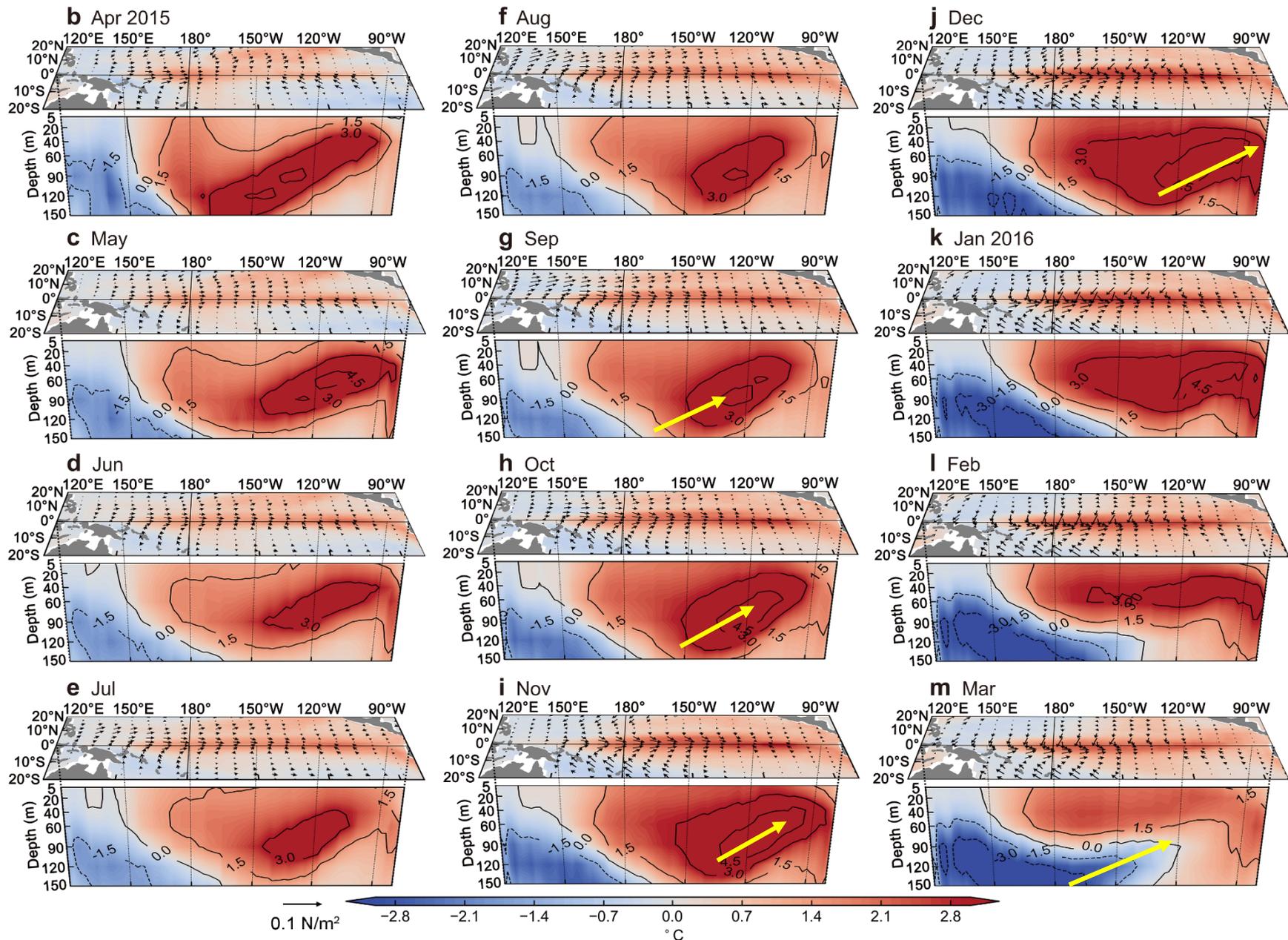
赤道垂直剖面

风应力-SST异常场

三维海温场



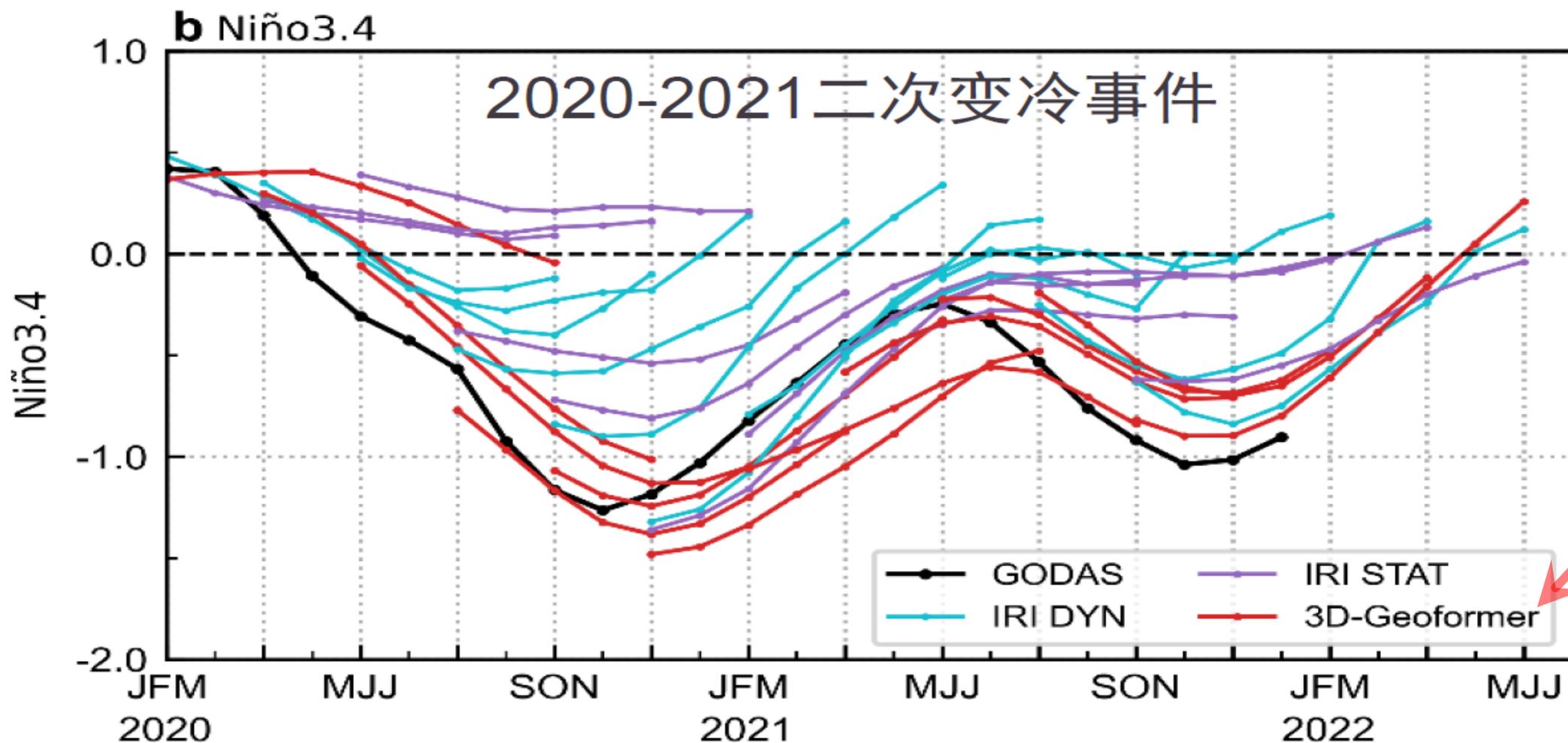
4.3 模型预测技巧评估: 2015-16年超强El Niño预测: 从2015年4月起报得到的演变



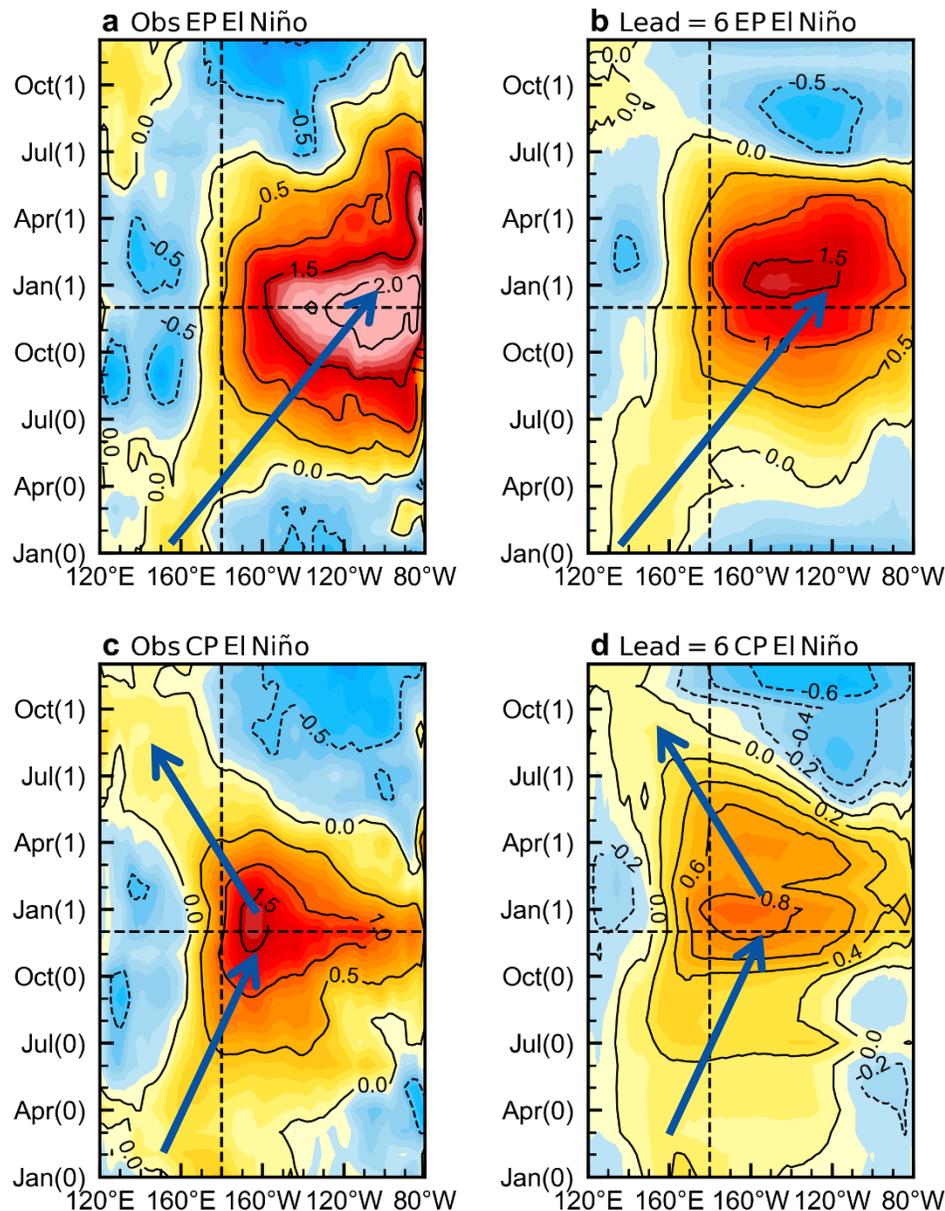
•该3D-Geoformer模型准确地预测了此次事件中的多变量场时空演变, 并正确捕捉到 ENSO演变中的**关键动力学过程**, 如风应力场与SST间的对应关系及次表层海温异常沿温跃层的传播过程等

•该个例分析充分展示了3D-Geoformer模型的三维多变量场预测的优势: 通过在模型构建中考虑海气**多变量耦合关系**, 模型成功地学习到基本的ENSO动力学知识, 保证了模型预测结果的**物理合理性与可信性**。

对双重和三重 La Nina 事件的个例预测



模型预测技巧评估：CP和EP型El Niño预测



EP与CP型El Niño中赤道SST异常时间演变：
左列为再分析数据；
右列为模型提前6个月的预测结果。
(a-b) EP型El Niño 合成结果；
(c-d) CP型El Niño 合成结果。

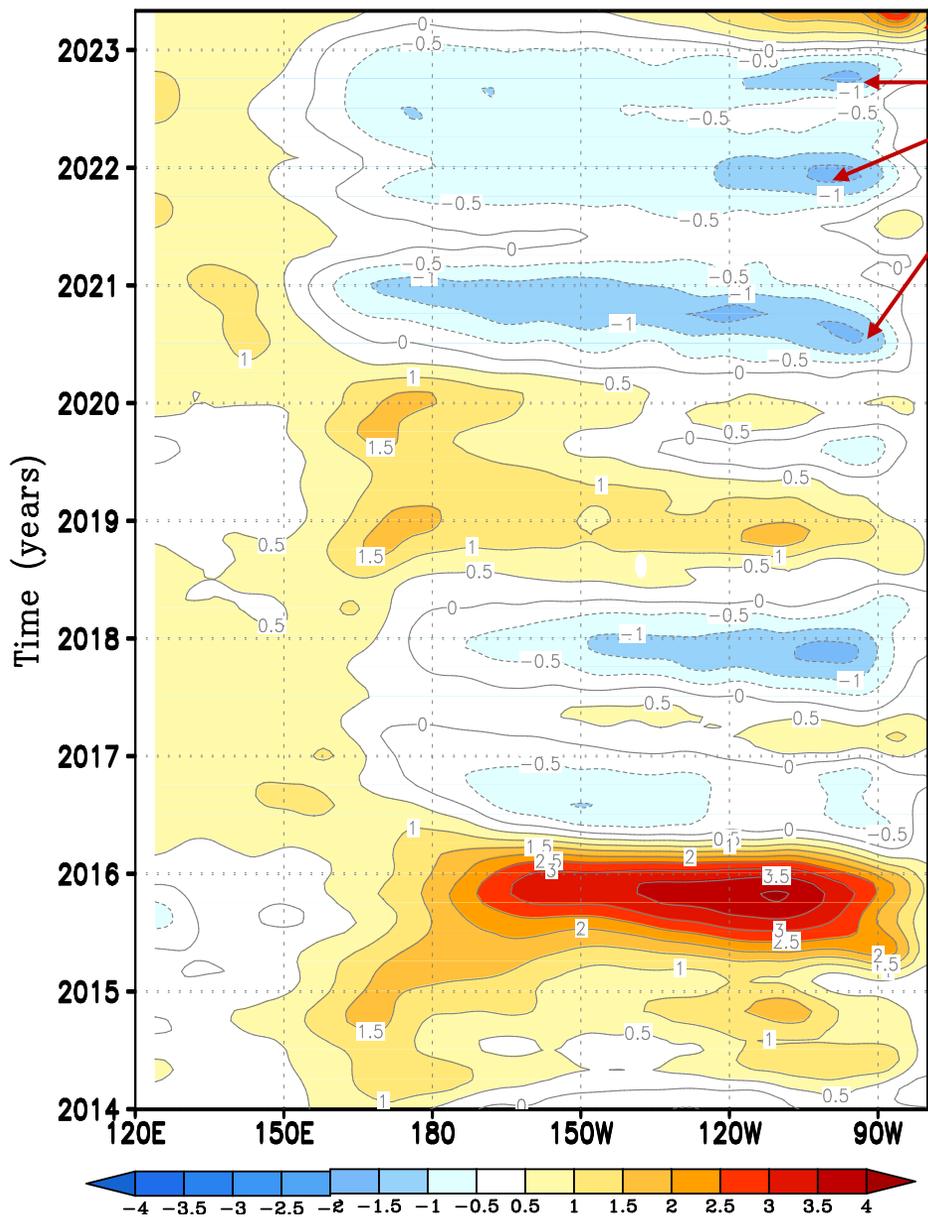
动力模式对ENSO多样性的模拟和预测一直存在较大偏差，本部分展示了数据驱动的3D-Geoformer 模型对两类El Niño预测的潜力，对进一步改善两类ENSO的预测有一定指导意义。

3D-Geoformer模型可以至少6个月对两类El Niño进行预测，并可以准确捕捉海温异常的空间演变、海温异常中心位置及强度等。

Real-time predictions: Observed evolutions

ERA5 SSTA: Jun. 2022-May. 2023

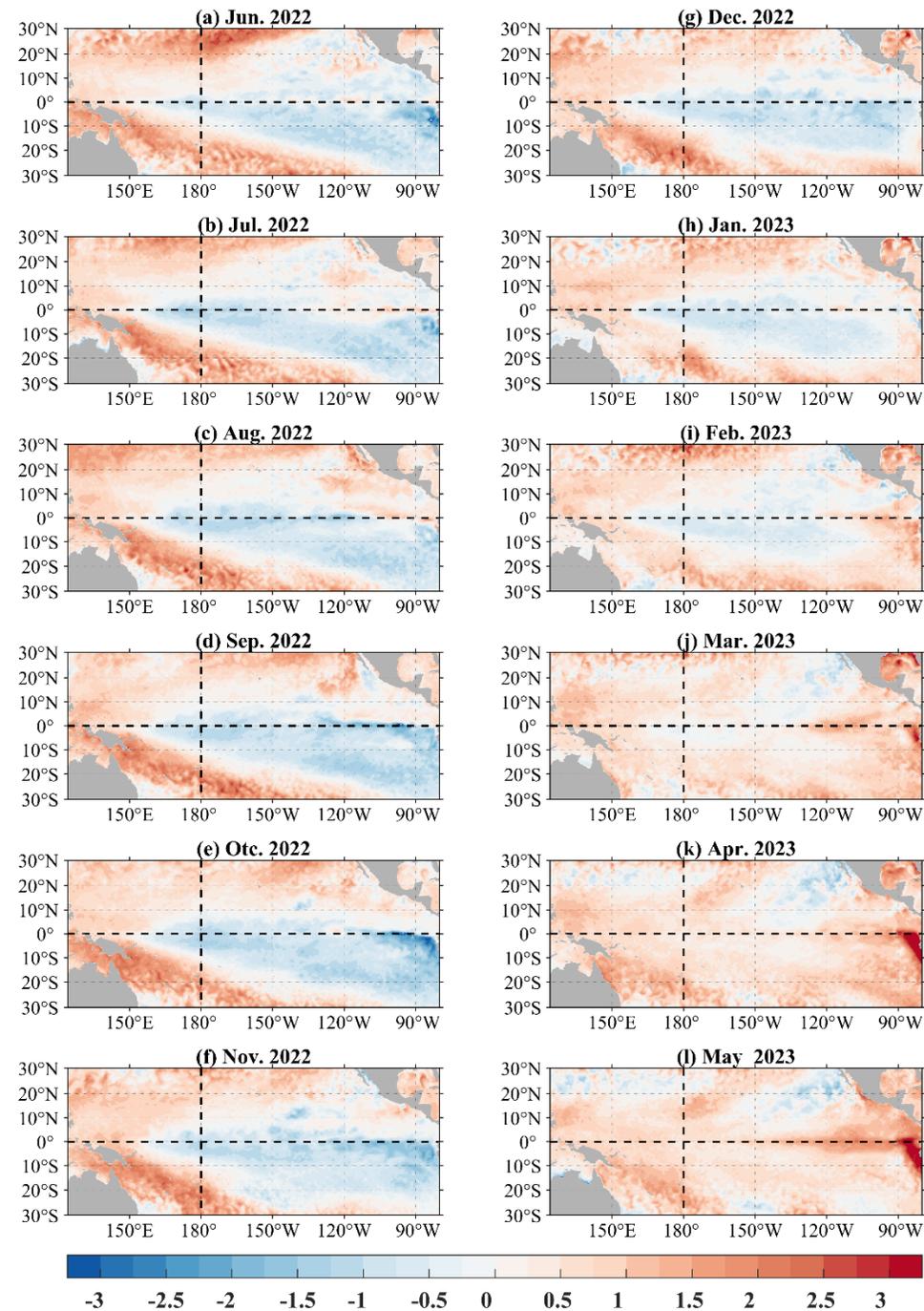
(a) SST anomalies along the equator



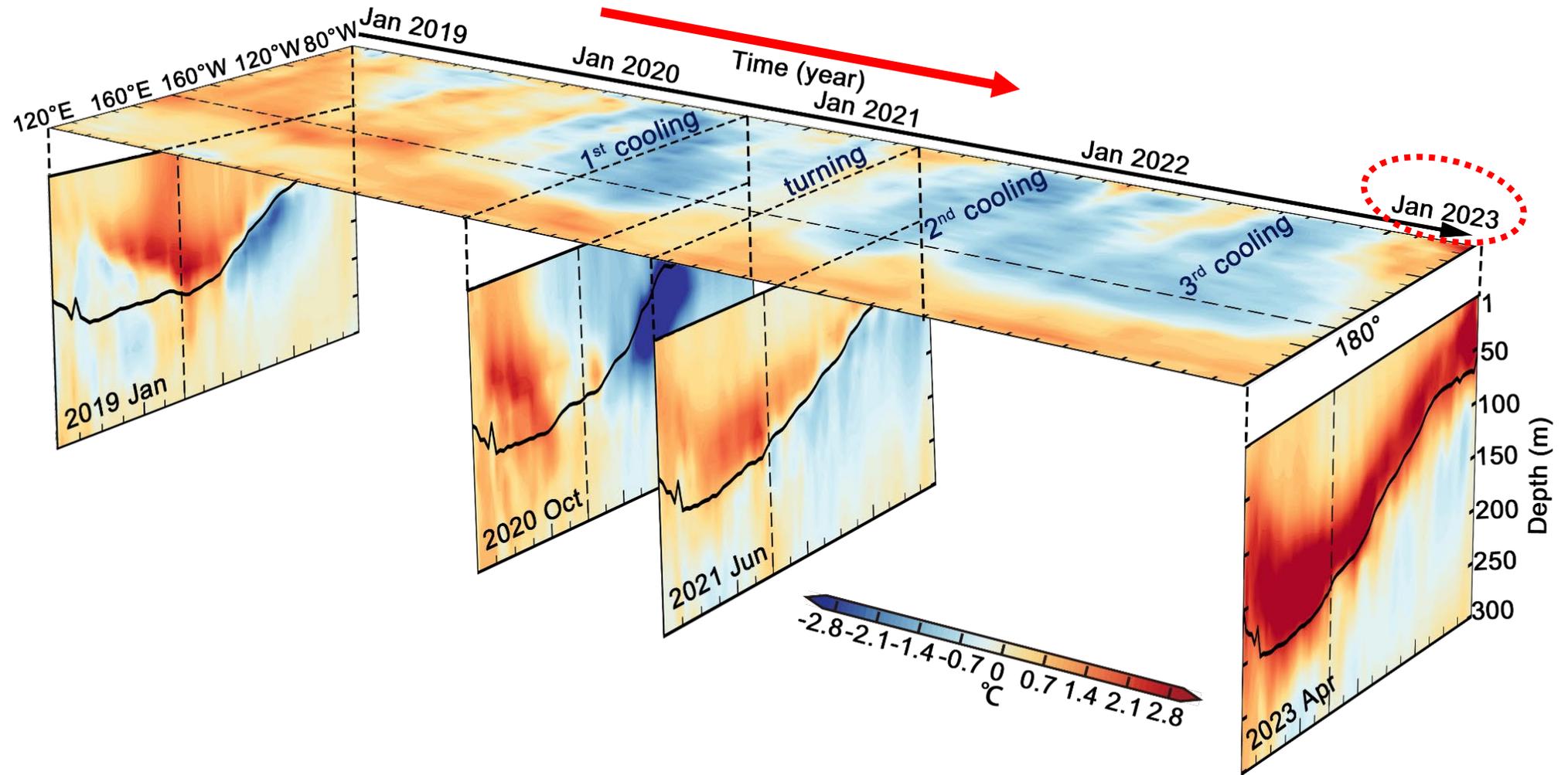
Warming

Triple cooling events

- Real-time SSTa evolutions updated to May 2023 →

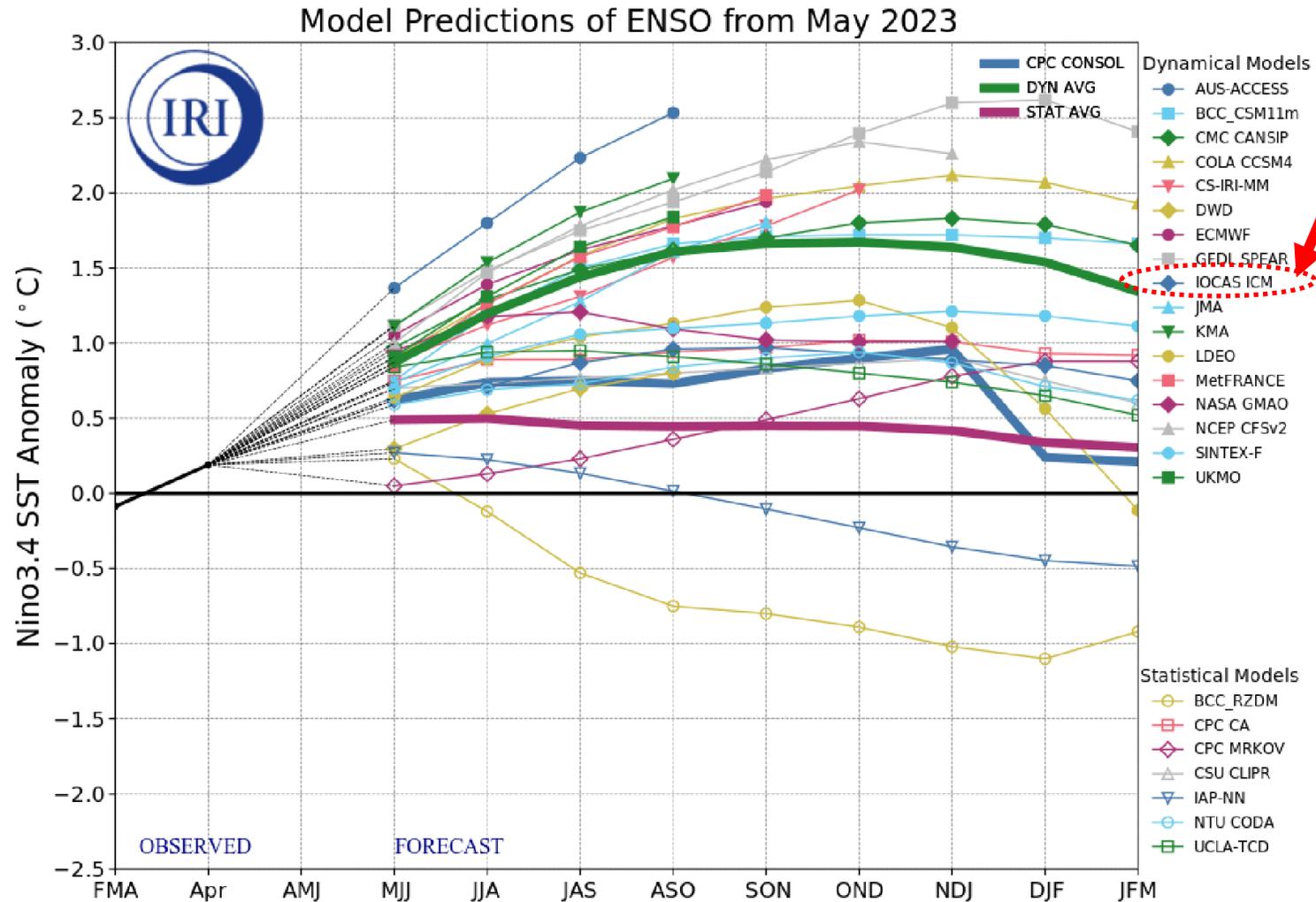


Real-time predictions: Observed evolutions



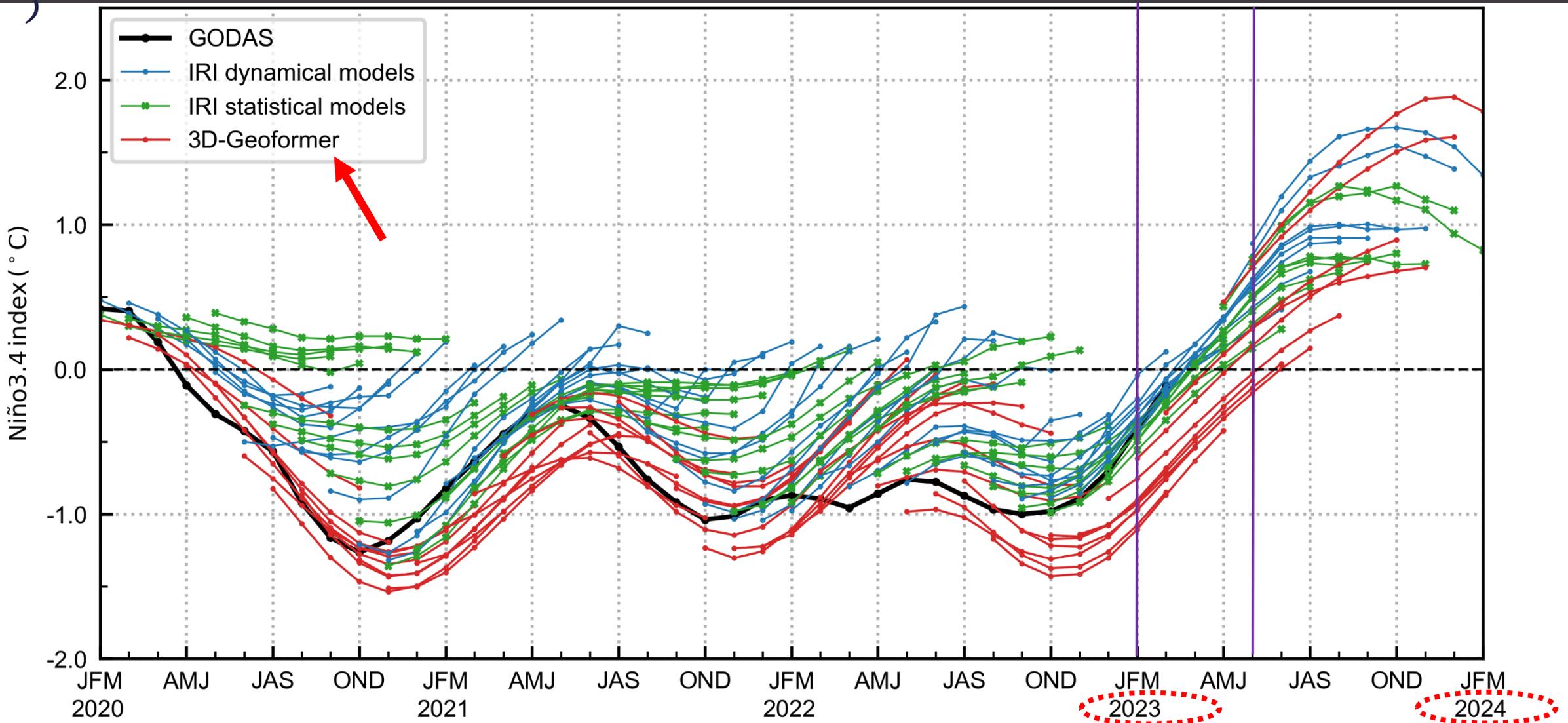
- Temperature anomaly evolution from January 2019 to April 2023 for the zonal-time section at the sea surface and zonal-depth sections along the equator.

4.6 Real-time predictions: IRI collections, including IOCAS ICM (Intermediate coupled model)



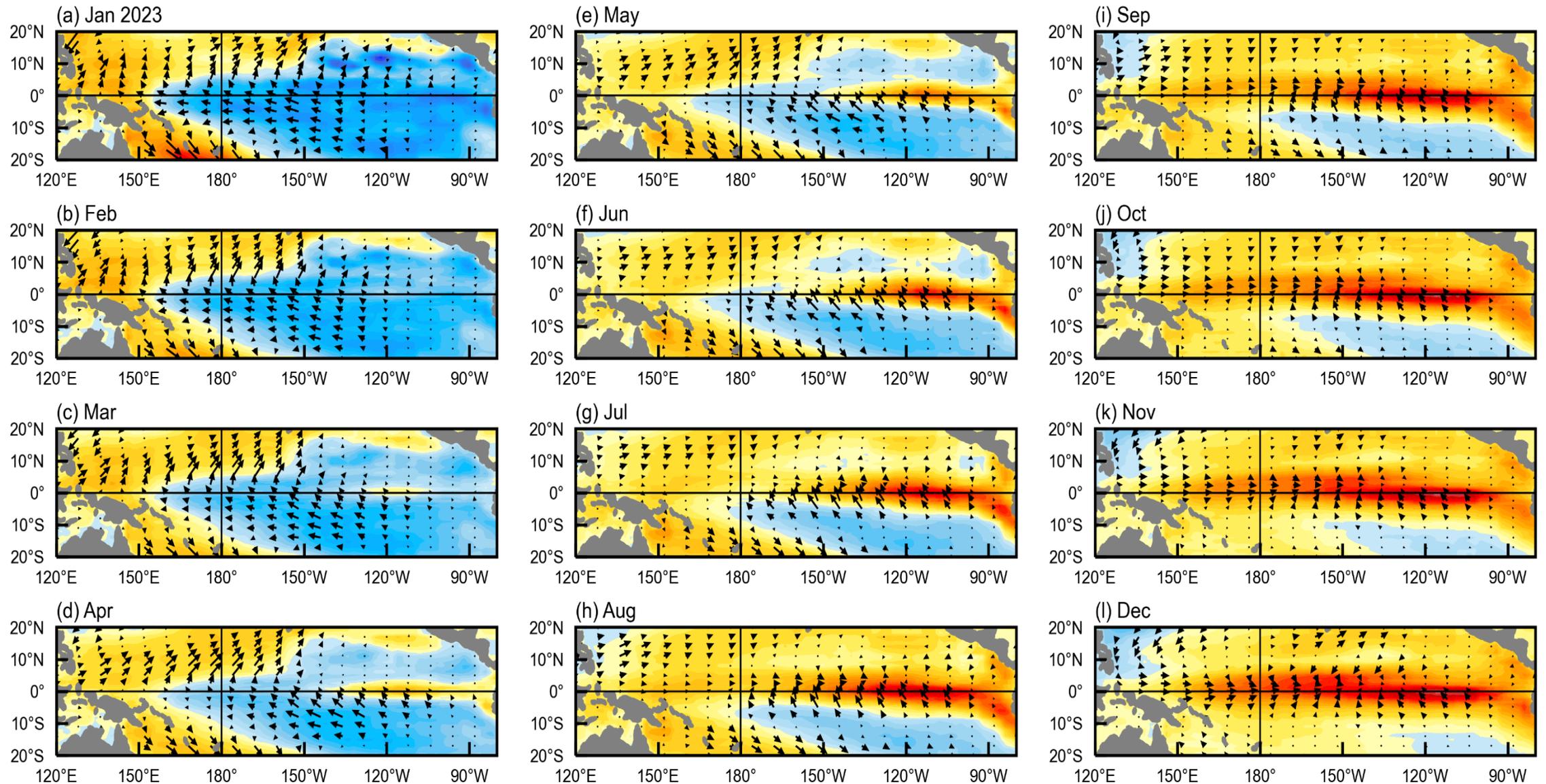
- Predictions of SST anomalies for the Niño 3.4 region. Figure updated by International Research Institute (IRI) for Climate and Society.

4.6 Real-time predictions: 3D-Geoformer (实时预测)

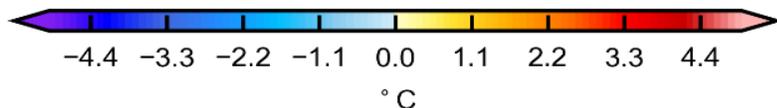
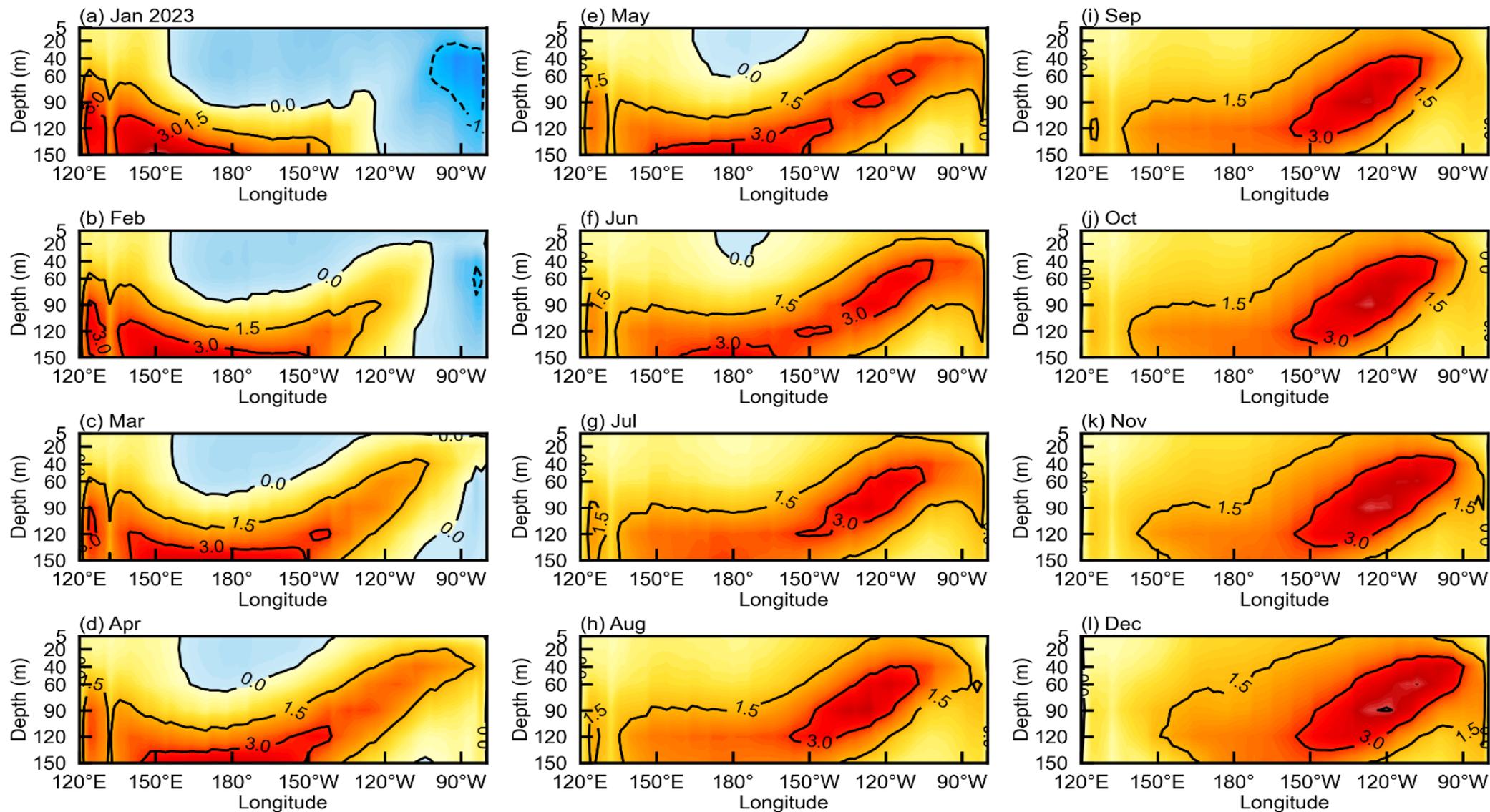


ORAS5 reanalysis (black lines) and predicted (colored lines) Niño3.4 SST anomalies during 2020-2023. The blue and green lines indicate the predictions made by dynamical and statistical models from the IRI collection, and the red lines indicate the predictions made using 3D-Geoformer.

使用3D-Geoformer (TI=12) 从2023年1月起报得到的热带太平洋海表温度&风应力异常演变

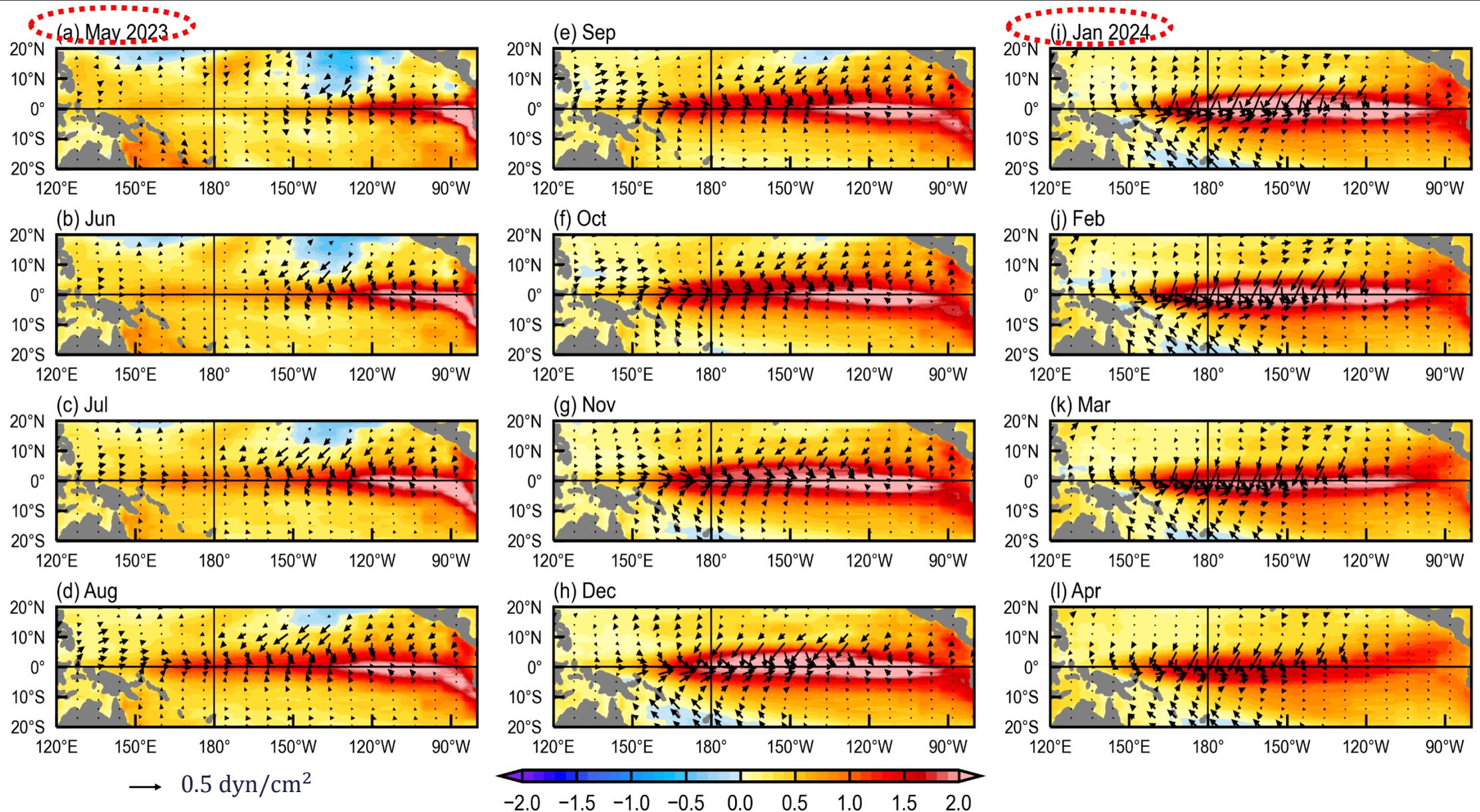


使用3D-Geoformer (TI=12) 从2023年1月起报得到的赤道太平洋垂向剖面上的海温异常演变



4.6 Real-time predictions: 3D-Geoformer

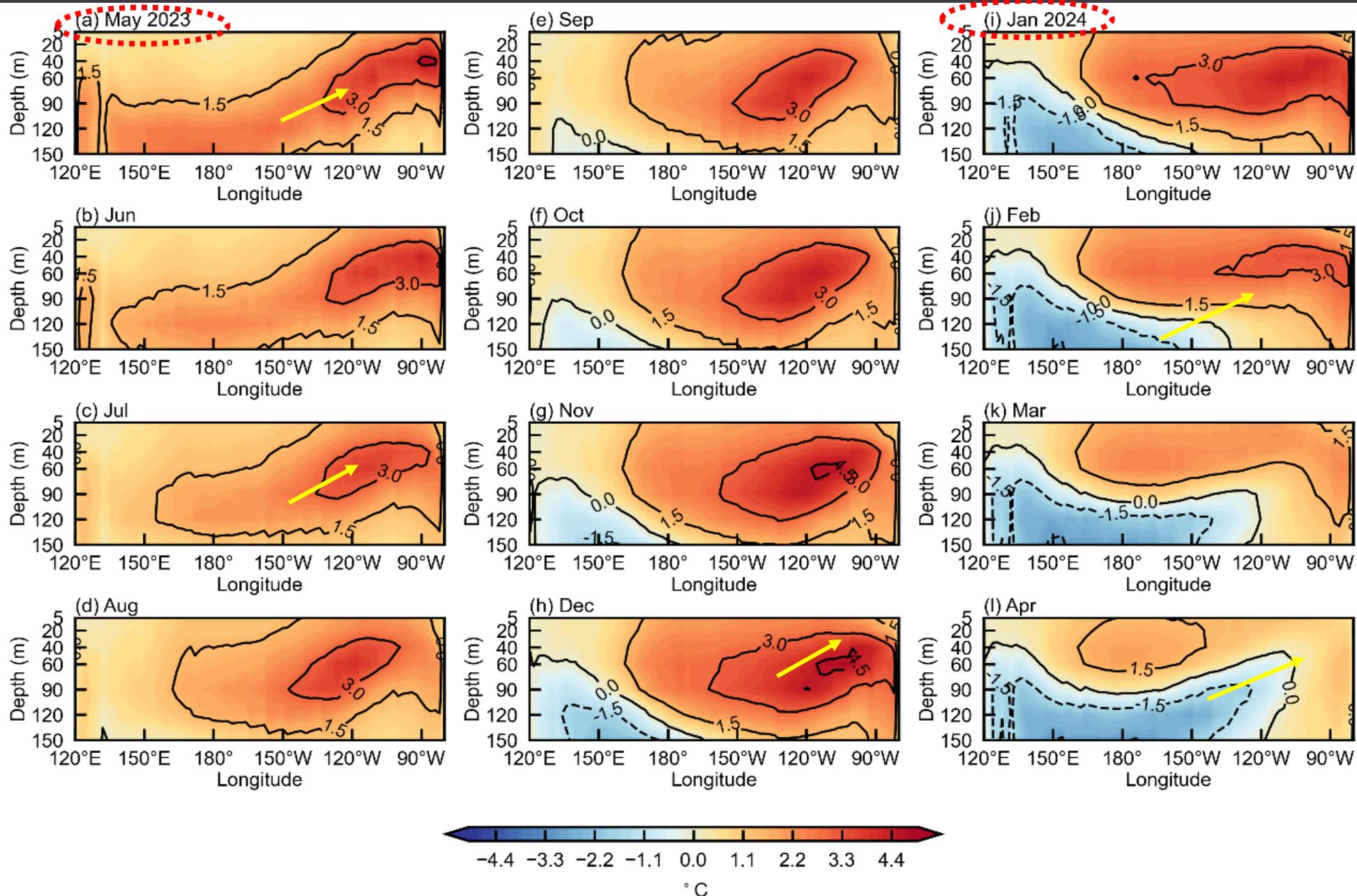
Predicted from May 2023



➤ Horizontal distributions of SST (shading) and wind stress (vectors) anomalies during 2023-2024

4.6 Real-time predictions: 3D-Geoformer

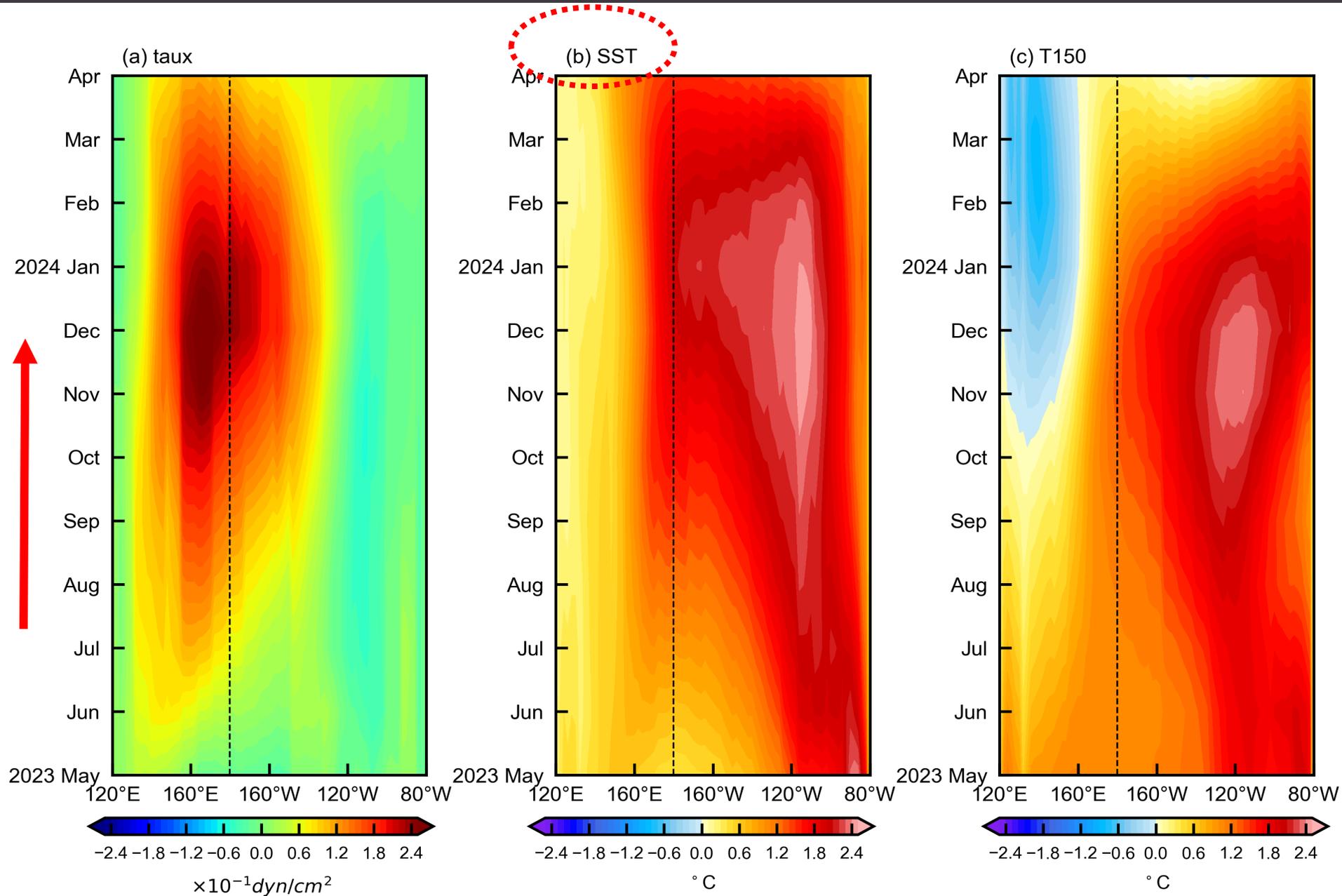
Predicted from May 2023



➤ Zonal-depth sections of upper-ocean temperature anomalies along the equator predicted by 3D-Geoformer

4.6 Real-time predictions: 3D-Geoformer

Predicted from May 2023



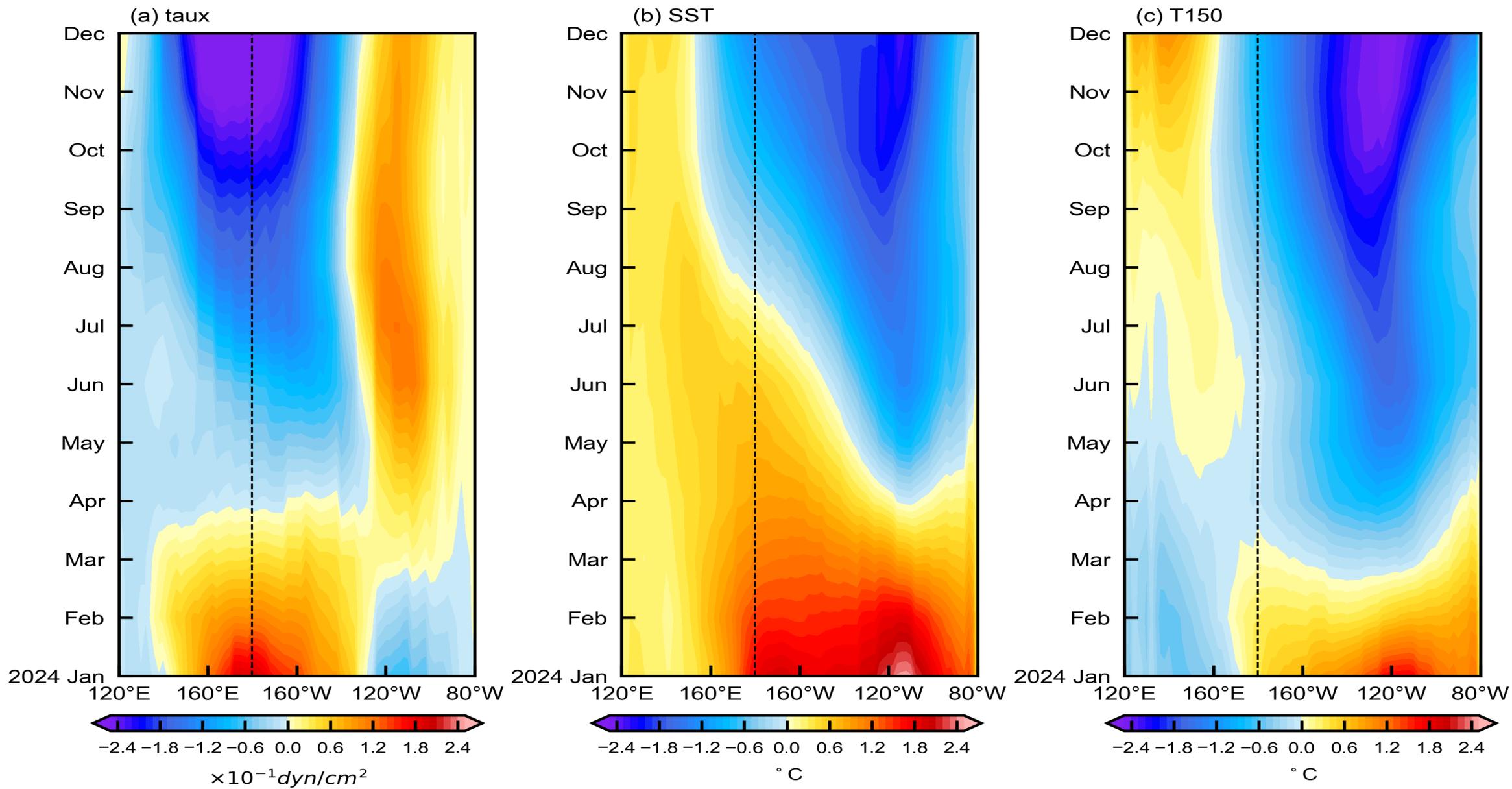
➤ Zonal-time sections on the equator:

(a) zonal wind stress,

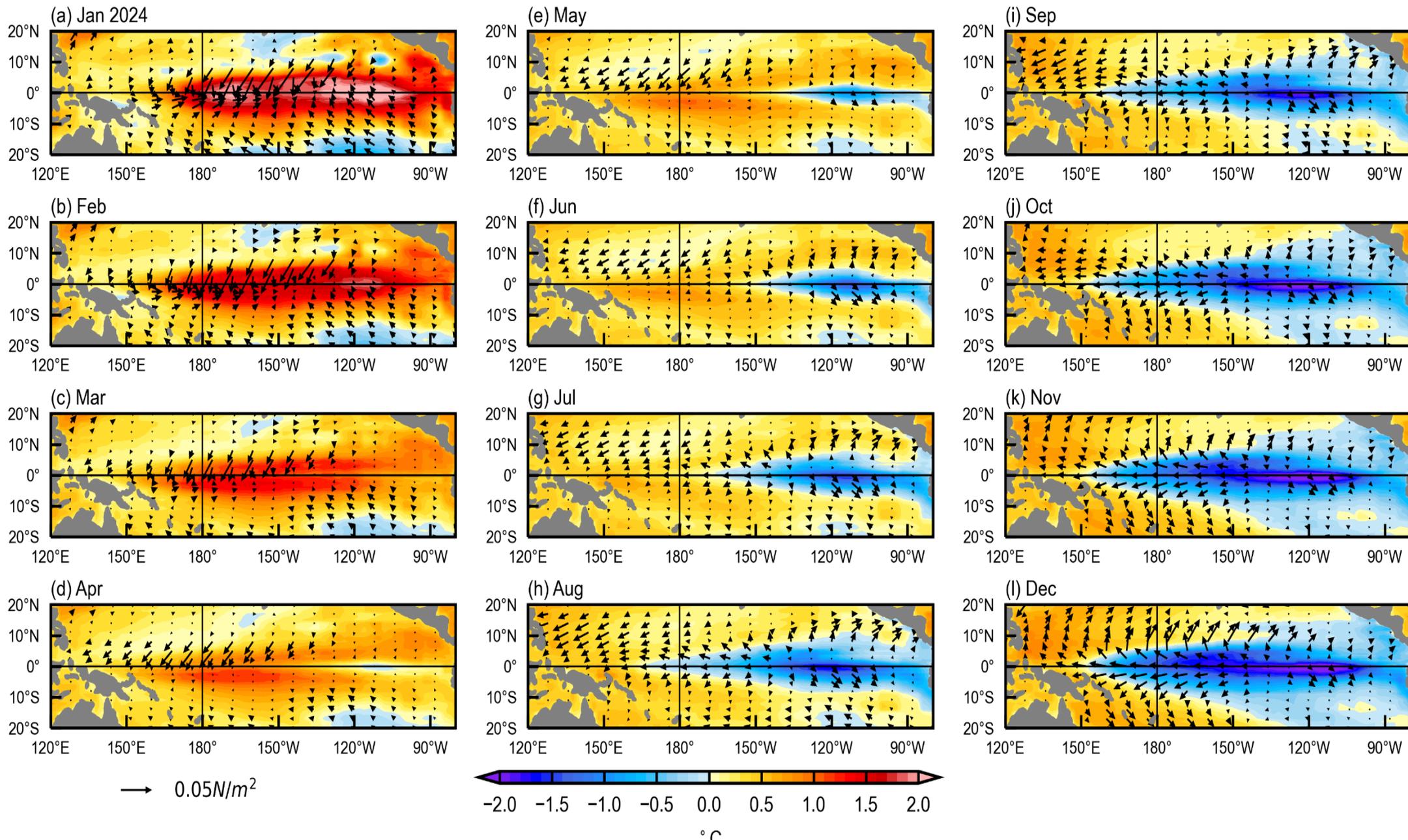
(b) SST,

(c) the average temperature of the upper 150 m (T150) anomalies.

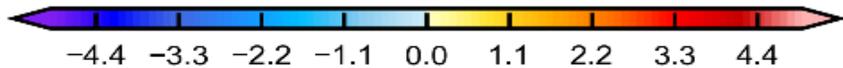
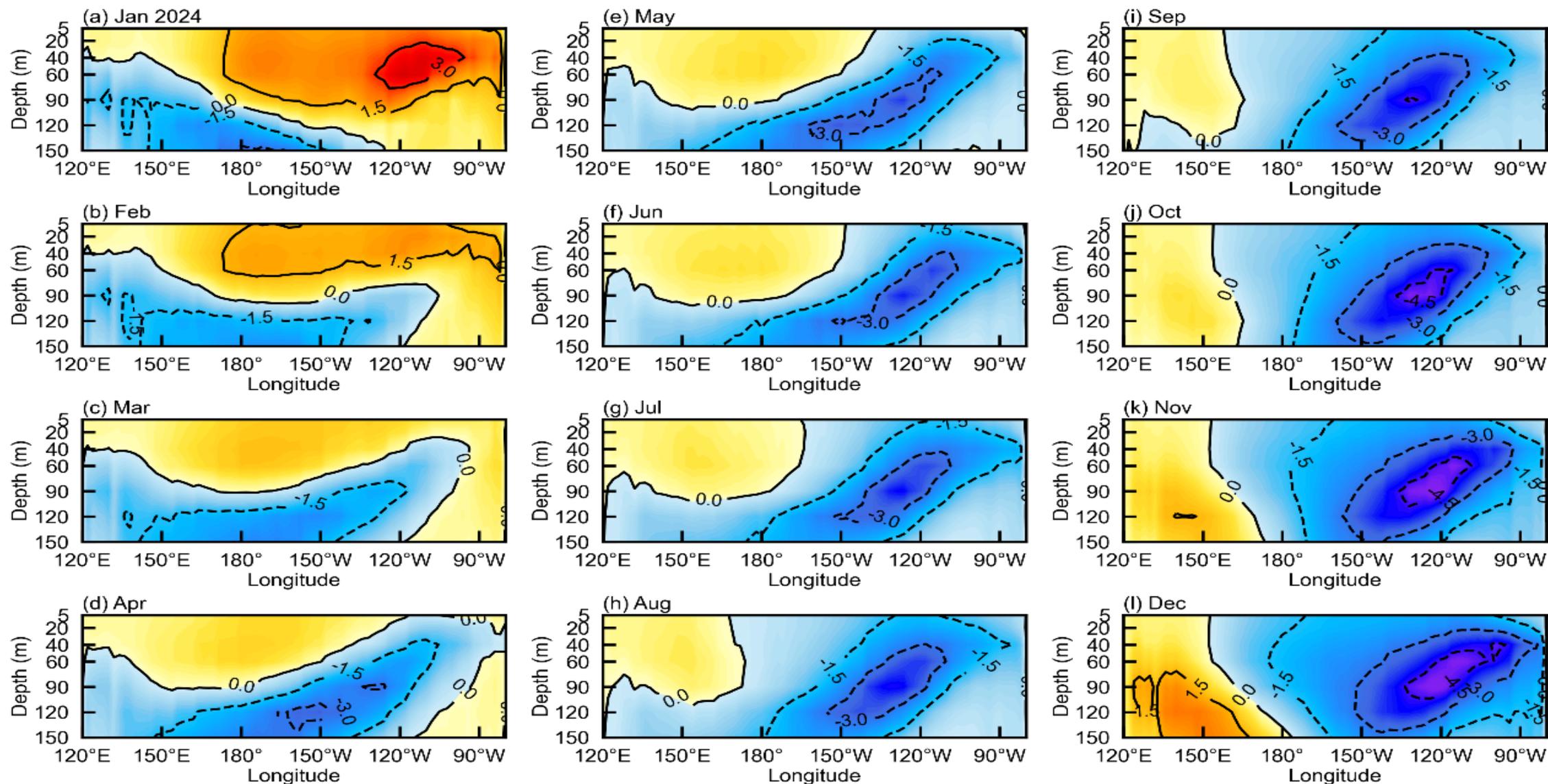
使用3D-Geoformer (TI=12) 从2024年1月起报得到的赤道太平洋：纬向海表风应力、海表温度和上层150米平均温度异常 (T150) 演变



使用3D-Geoformer (TI=12) 从2024年1月起报得到的热带太平洋海表温度&海表风应力异常演变



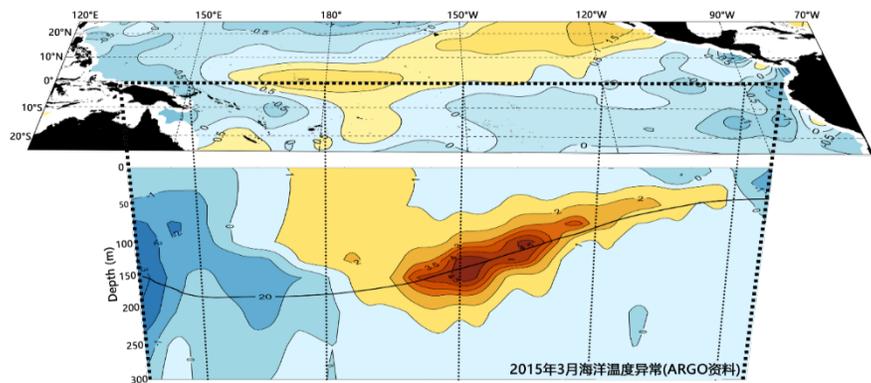
使用3D-Geoformer (TI=12) 从2024年1月起报得到的赤道太平洋垂向剖面上的海温异常演变



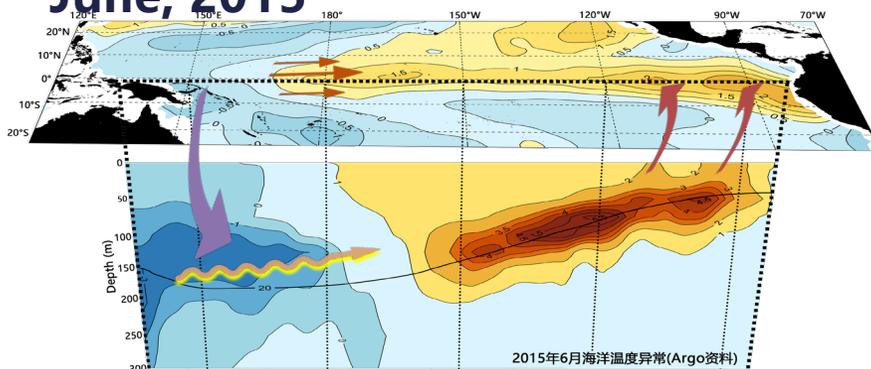
A Purely Data-driven **Transformer**-Based Coupled Ocean-Atmosphere Model for ENSO Research

多月的多变量做为初条件: TI=12个月

March, 2015



June, 2015

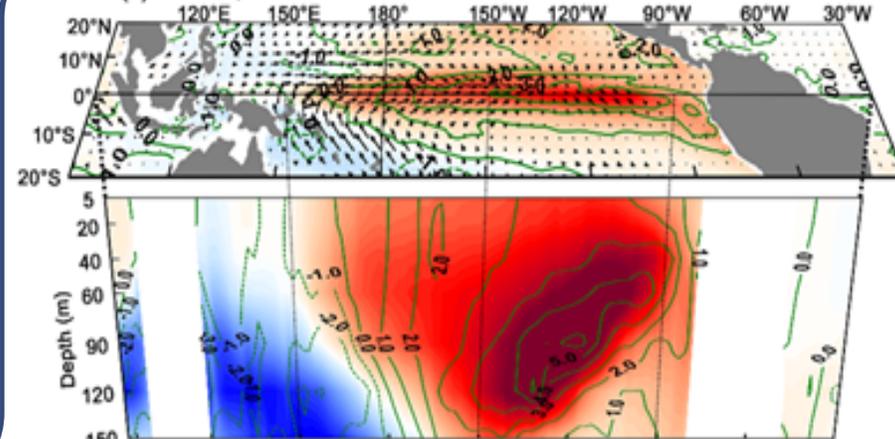


12个
月输
入场

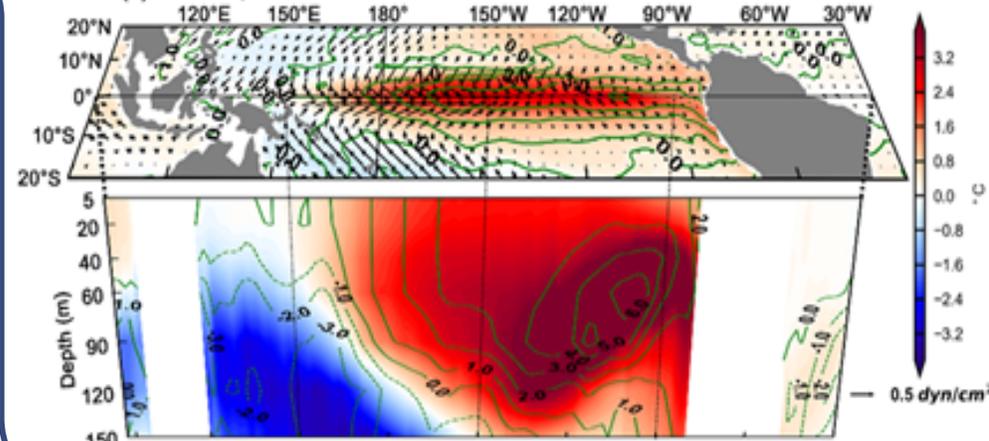
20个
月输
出场

多变量逐月滚动预测

(d) Oct 2015; lead=7 mon



(e) Dec 2015; lead=9 mon



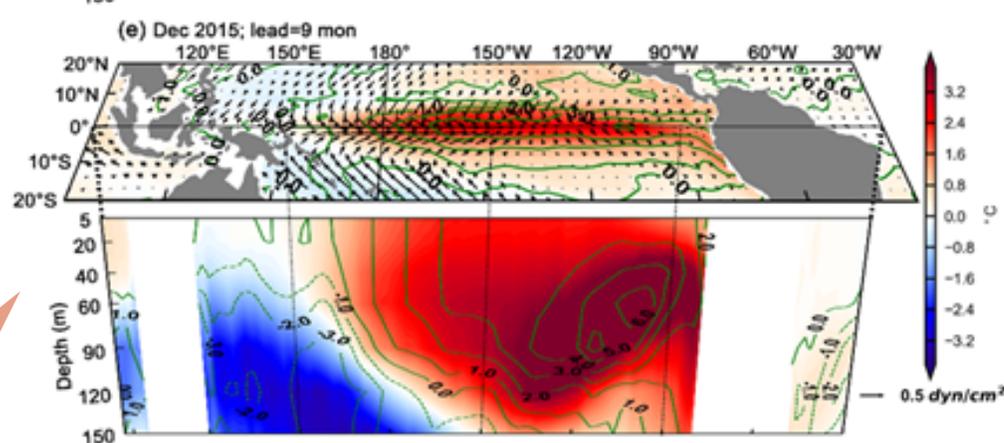
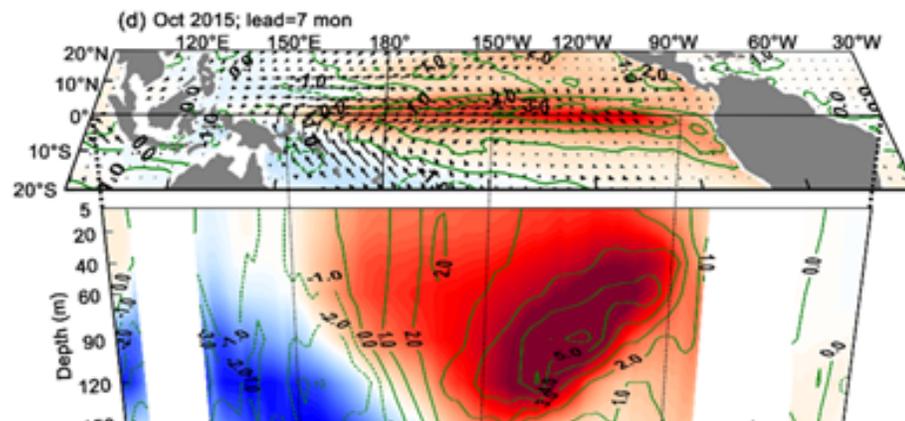
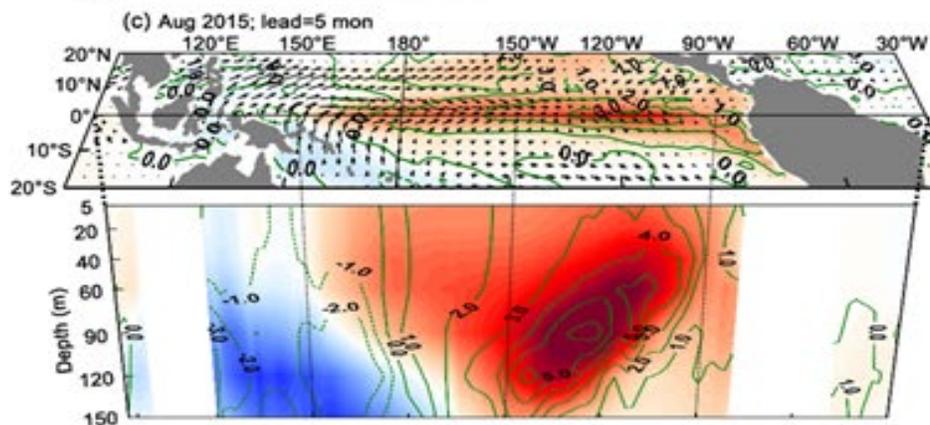
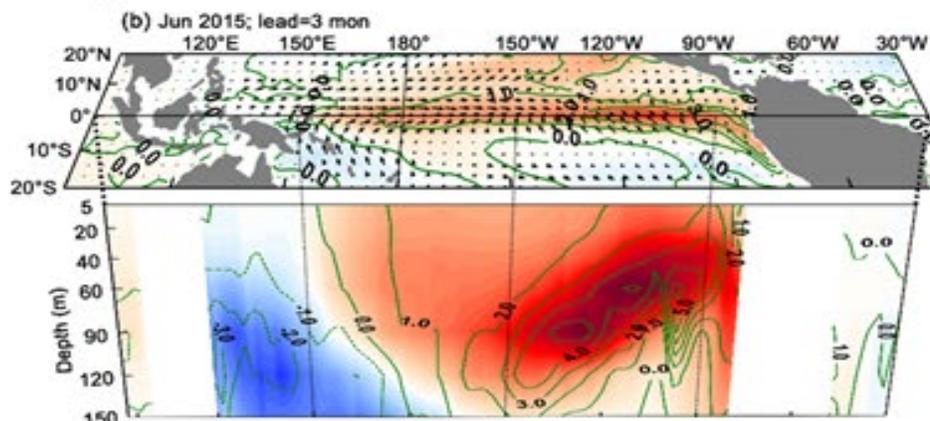
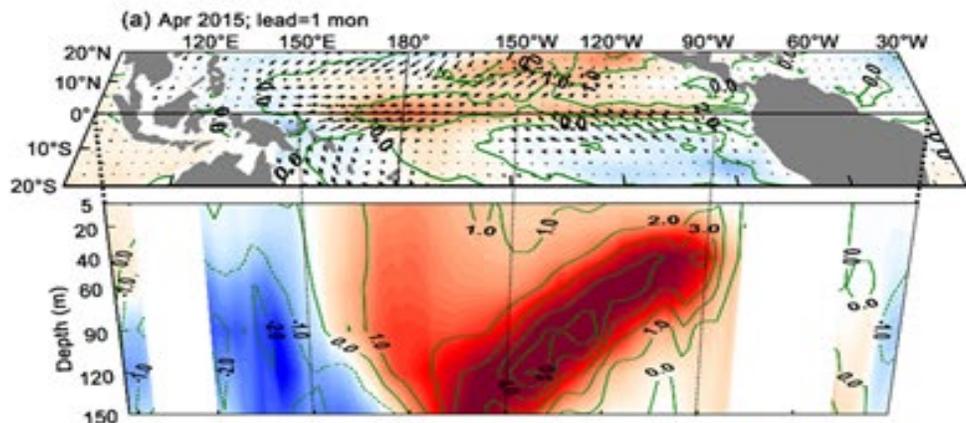
特色、优势和应用： a new modeling tool

纯数据驱动、基于transformer构架的海气耦合模式
(命名为3D-Geoformer)，并用于ENSO相关的三维海温
场及其与海表风场等多变量耦合的表征和预测

- ✓多变量三维海温场等作为输入场（用做为预报因子）和输出场（用做为预报变量）；
- ✓采用深度学习（DL）领域中自注意力机制（transformer构架）以有效表征海气变量间非局部相互影响；
- ✓预测过程采用逐月滚动方式：在从预报因子到预报变量进行一个月的预测过程中，每月更新大气-海洋的输入场和输出场（即每月进行海气异常场交换和更新，实现了海洋与大气间的相互作用；
- ✓使用多时间段（窗口）中的前期海气信息以有效约束未来的演变，具有比基于数理方程的动力模式所无法实现的优势（动力模式难以做到的）；
- ✓敏感性试验以增强其可解释性。

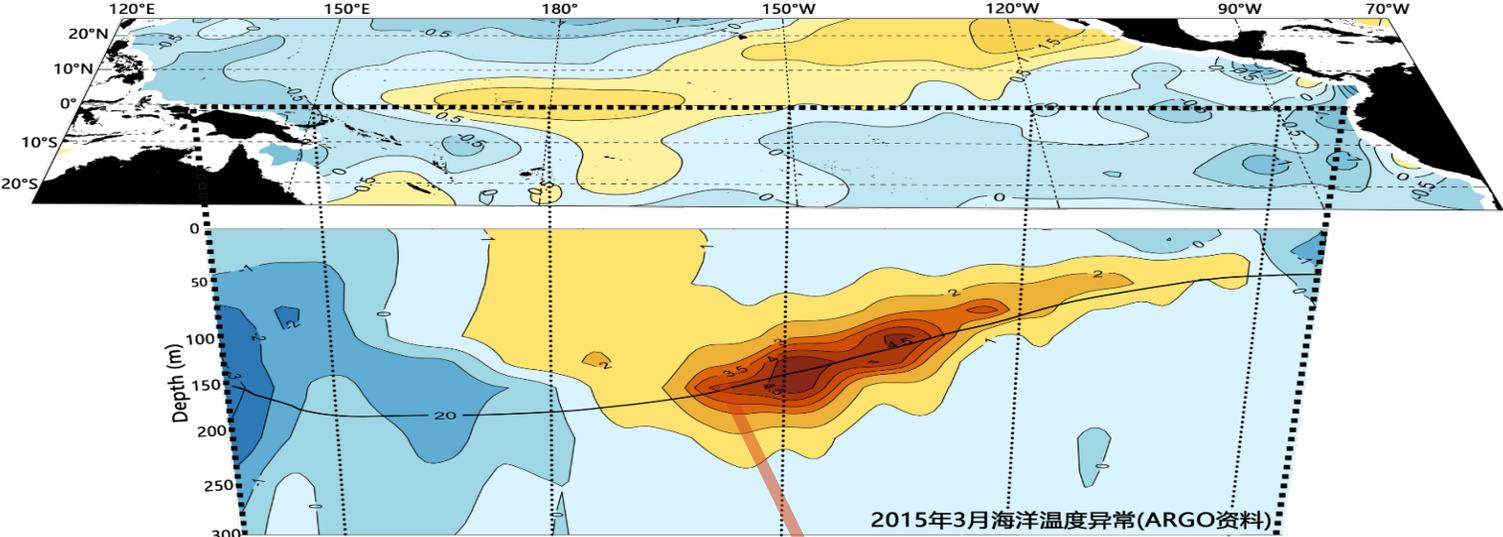
特点&优势：多变量逐月滚动预测表征海气相互作用

- Its ability to adequately represent the ocean-atmosphere coupling **within the DL-based modeling context: monthly coupling in a rolling way**

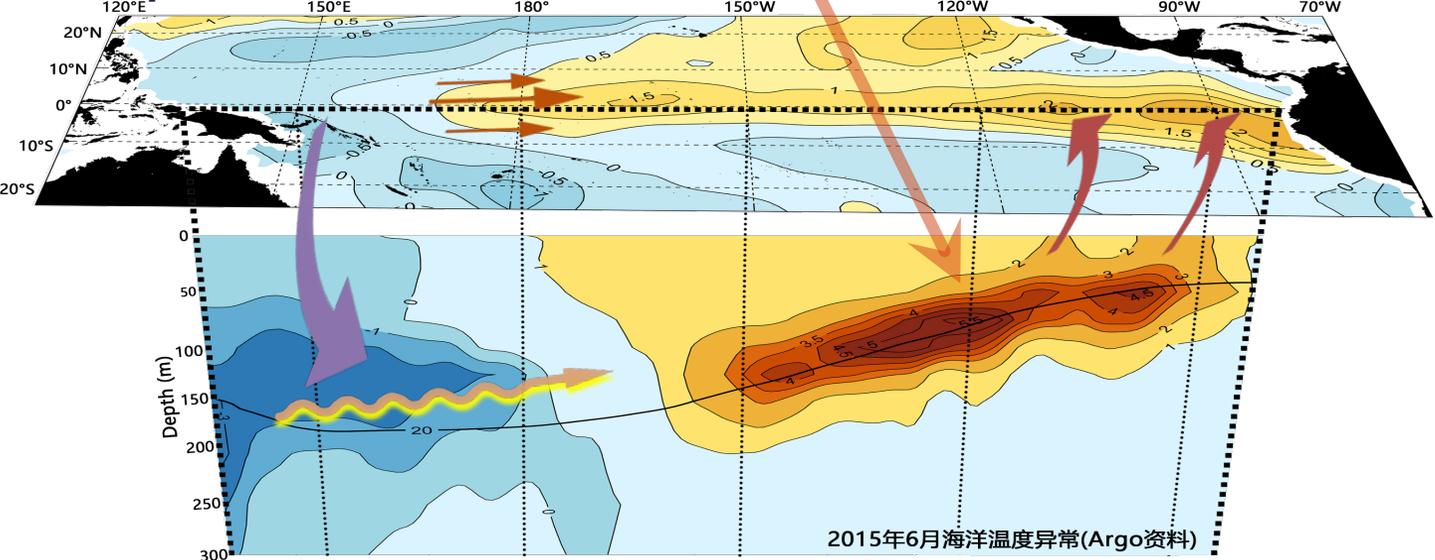


Argo data: upper-ocean temperature anomalies

March, 2015



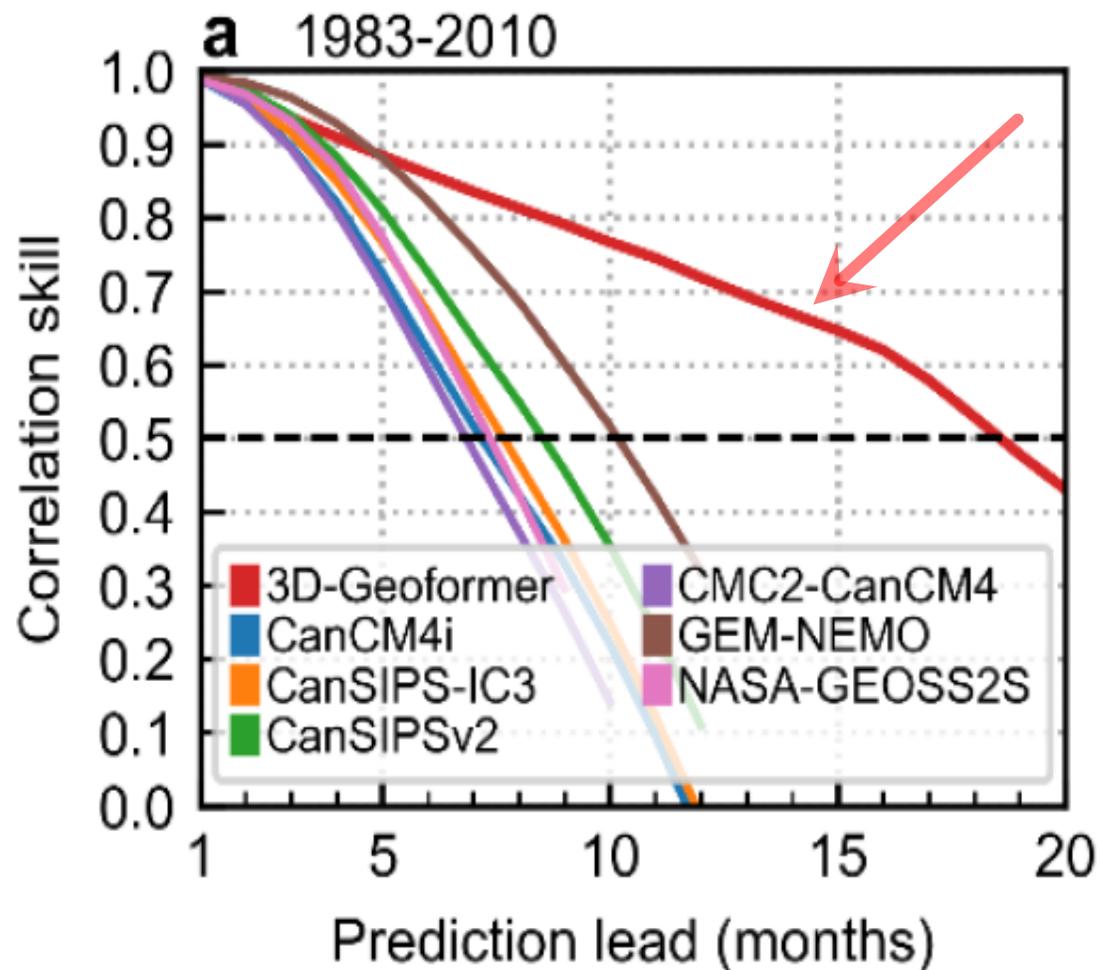
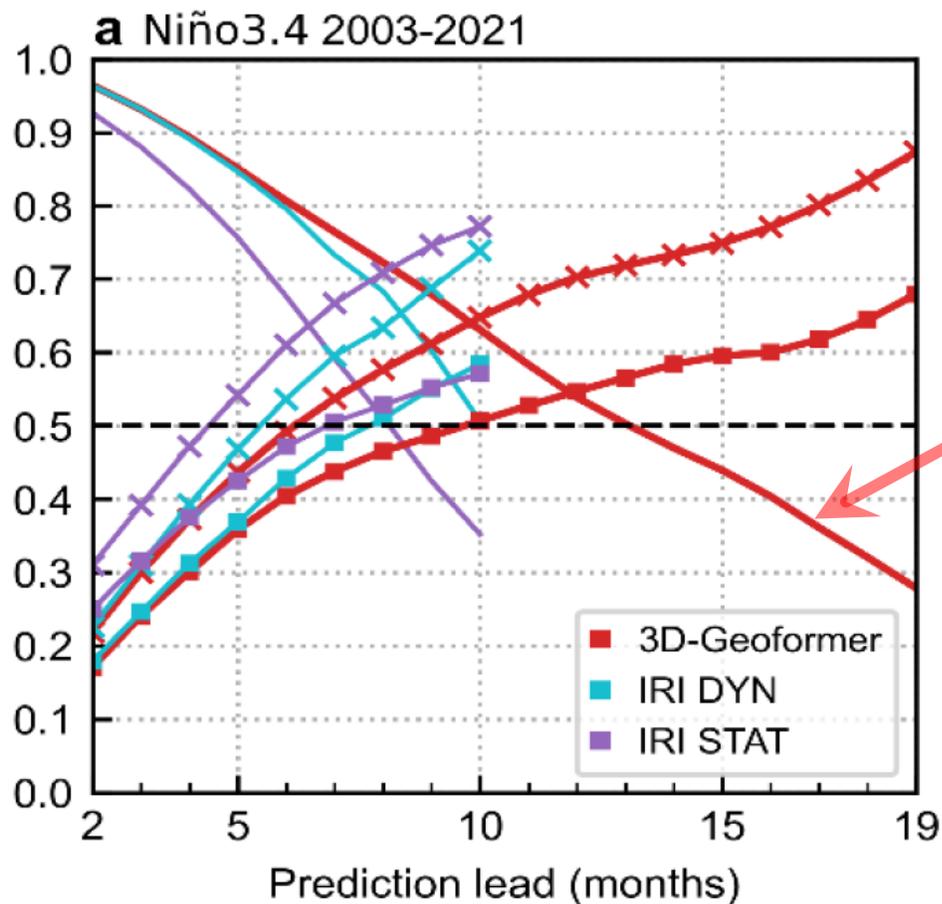
June, 2015



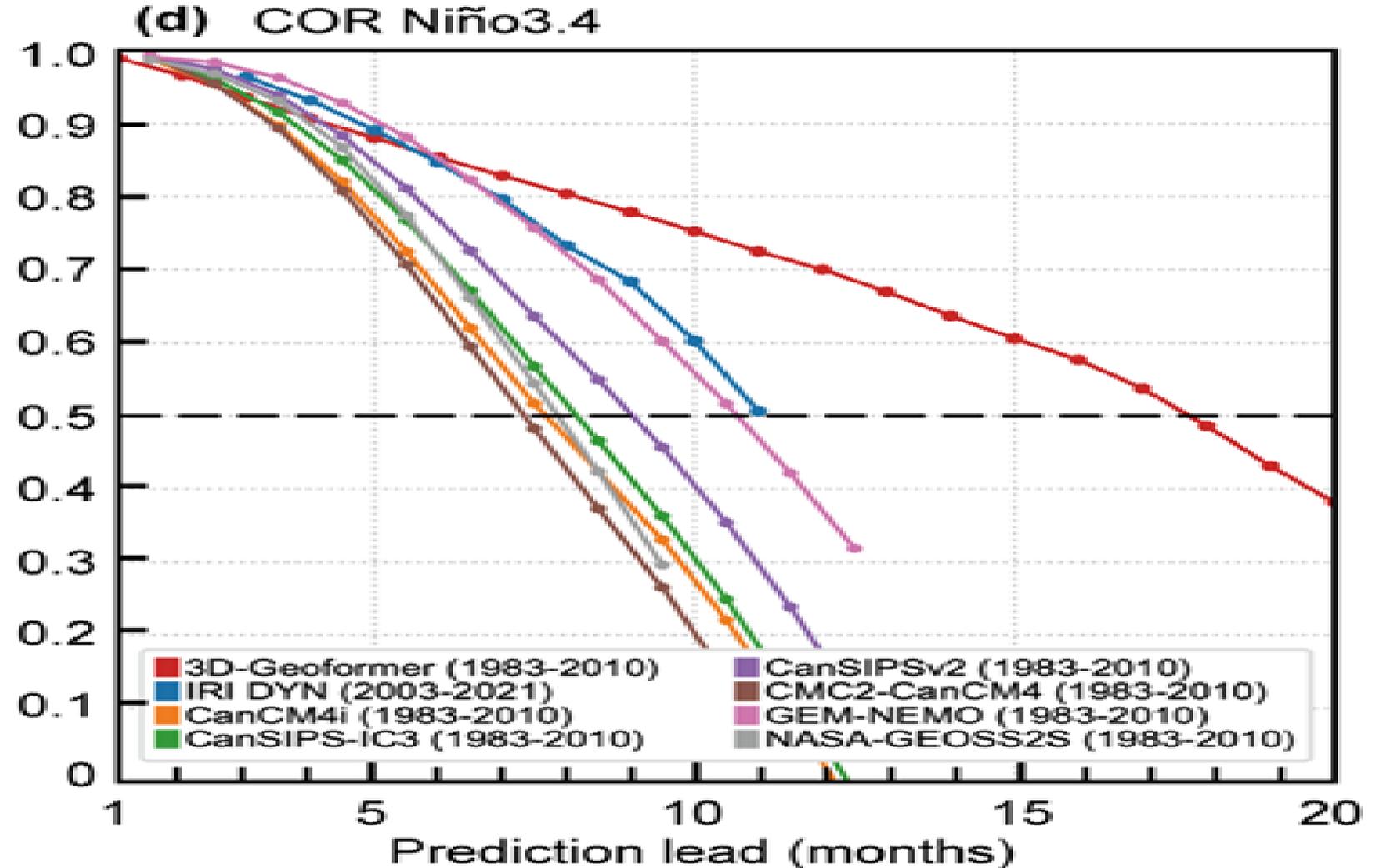
回报试验及比较

IRI/CPC 收集的统计/动力模式集合平均
对比：对ENSO有效预测时长更长，准
确度更高。

北美多模式集合（NMME）回报结果对比：对
SSTa 预测水平整体均优于当前先进的动力模式水
平，且随着提前预报时间的增长优势进一步扩大。

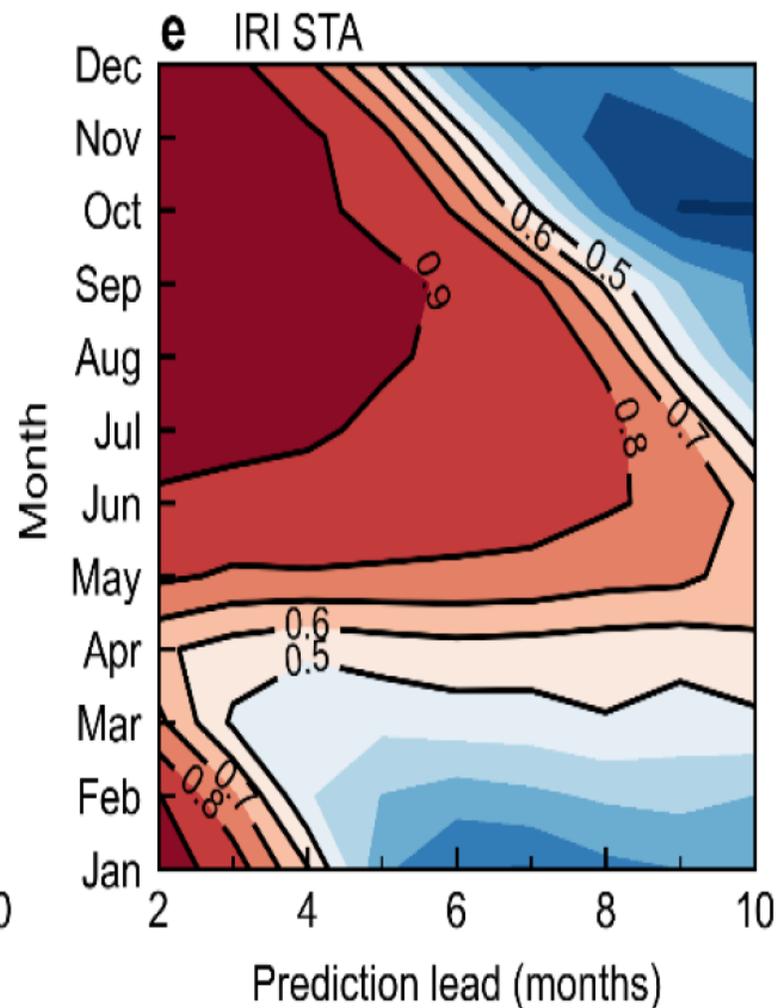
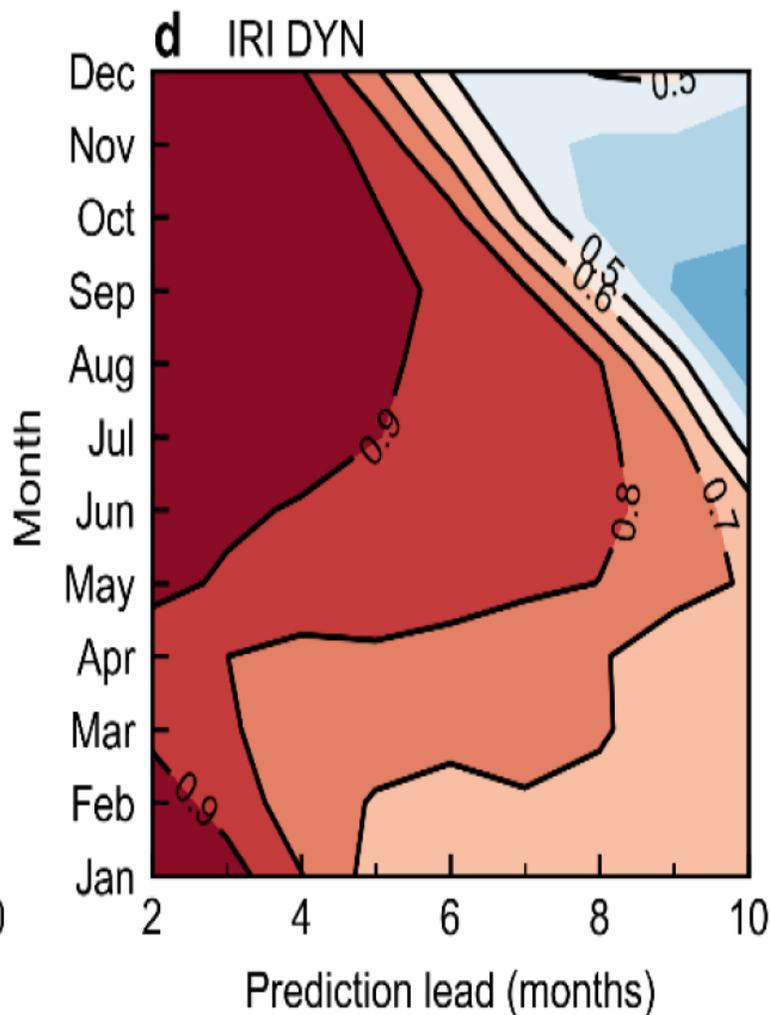
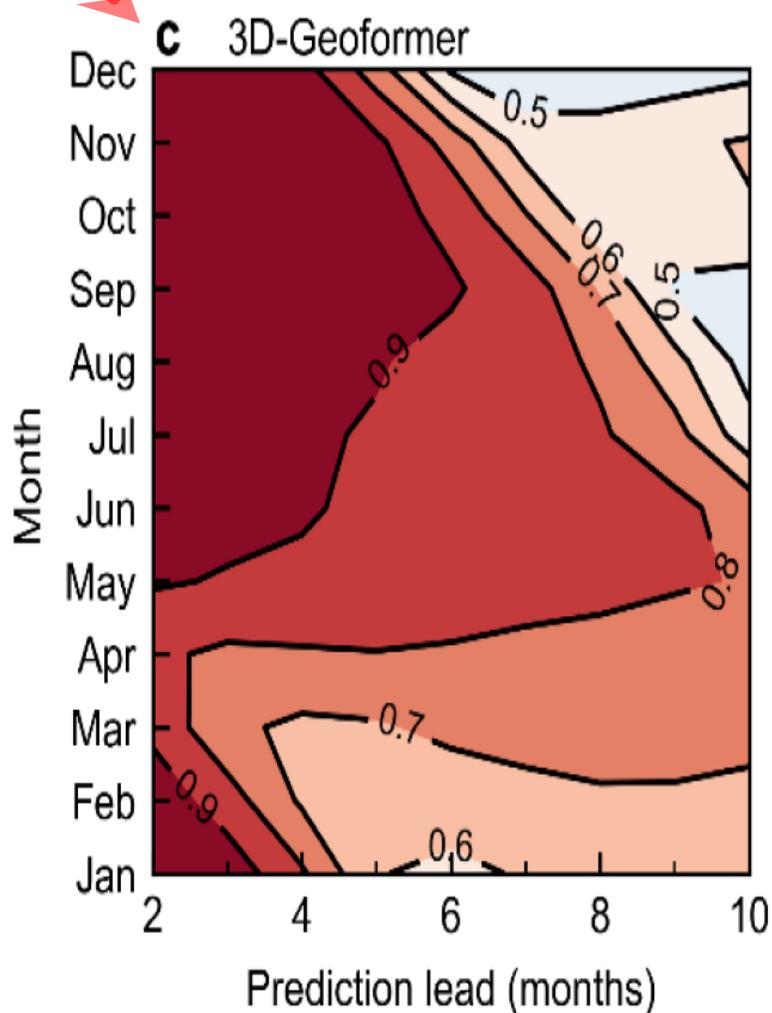


Retrospective hindcast experiments: surpassing other conventional statistical and dynamic models

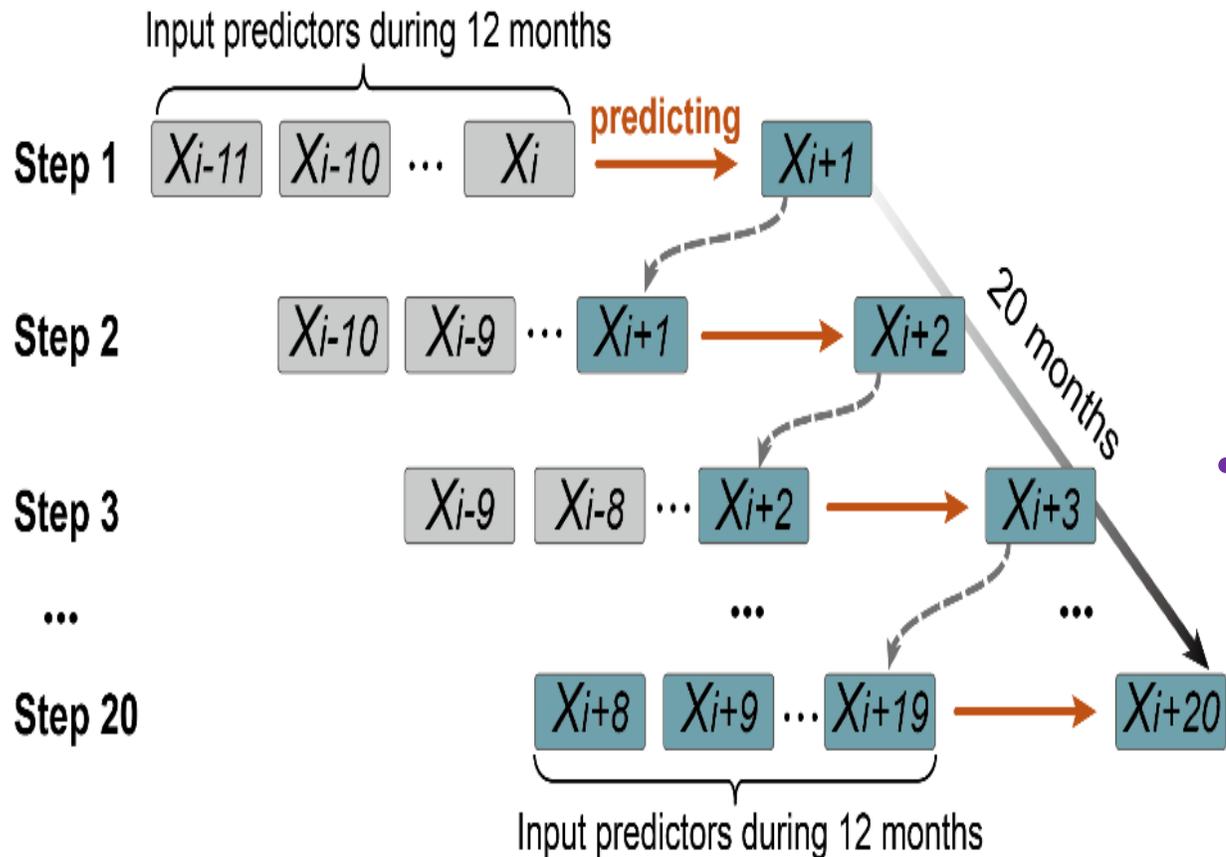


关于 ENSO 预测的春季预报障碍的改进

构建时还未考虑季节性!



初始场中使用多时间段（TI；窗口）中的前期三维时间序列信息



✓ 多变量**三维海温场**等作为输入场（预报因子）和输出场（预报变量）；

✓ 预测过程采用**逐月滚动**方式：在从预报因子到预报变量进行一个月的预测过程中，每月更新大气-海洋的输入场和输出场（即每月进行海气异常场交换，实现了海洋与大气间的相互作用；

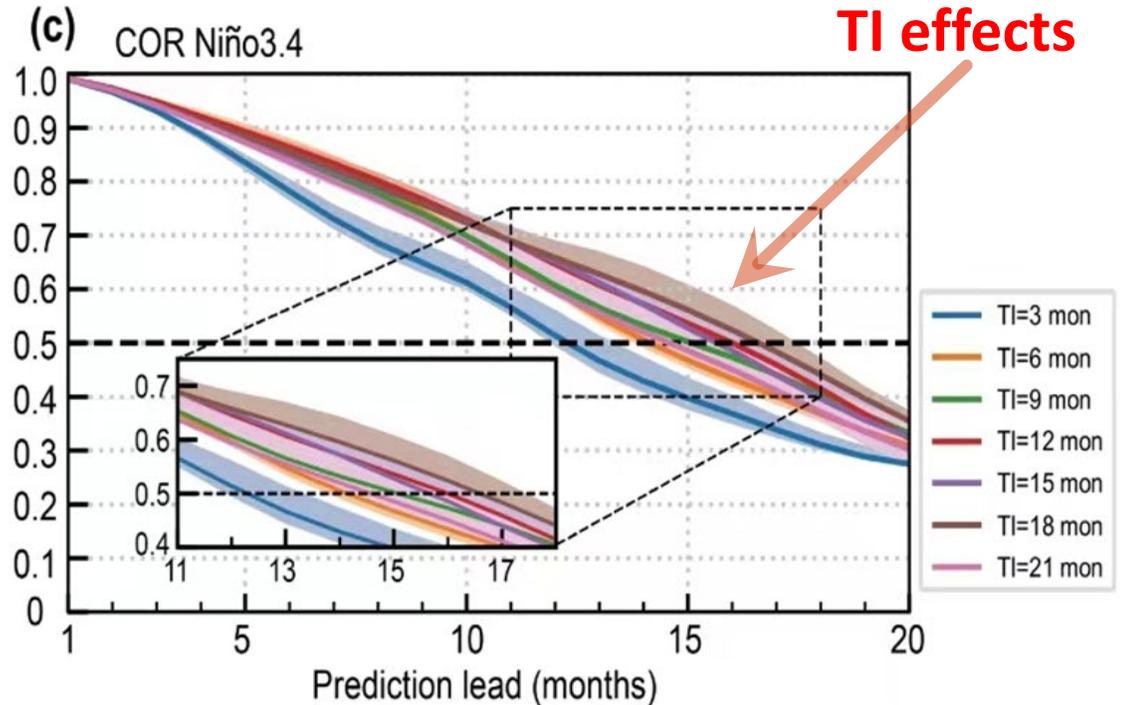
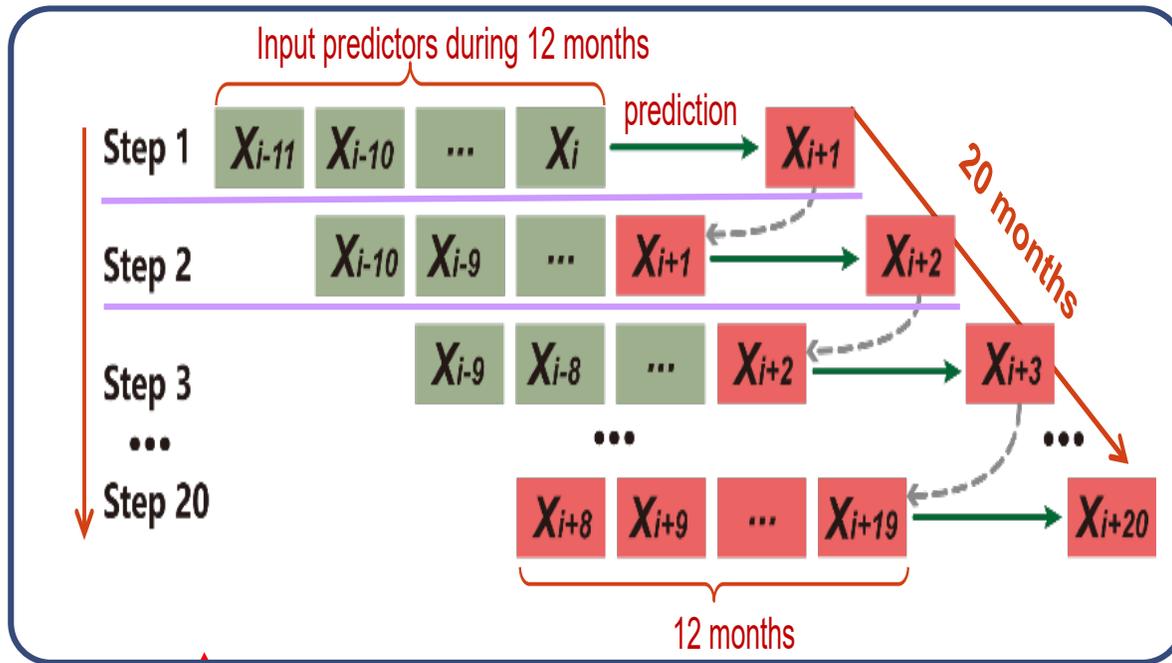
✓ 初始场中使用多时间段（TI；窗口）中的前期三维时间序列信息



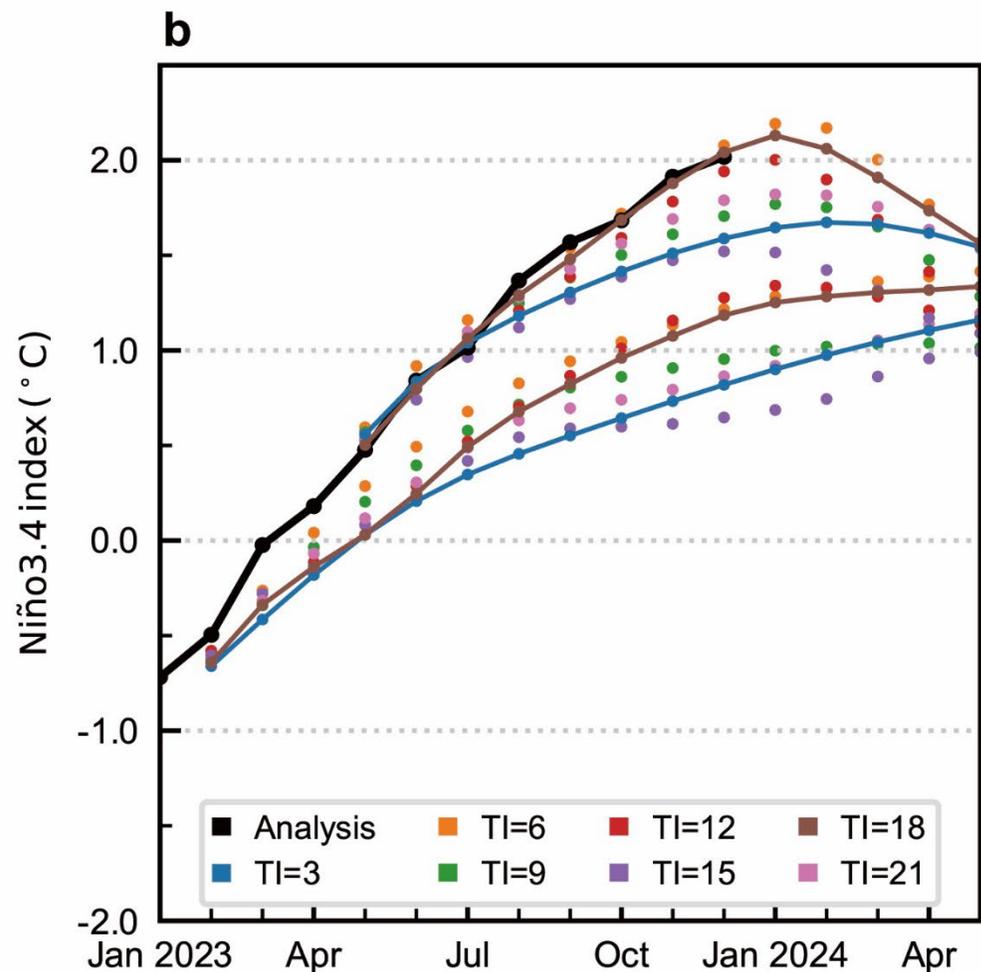
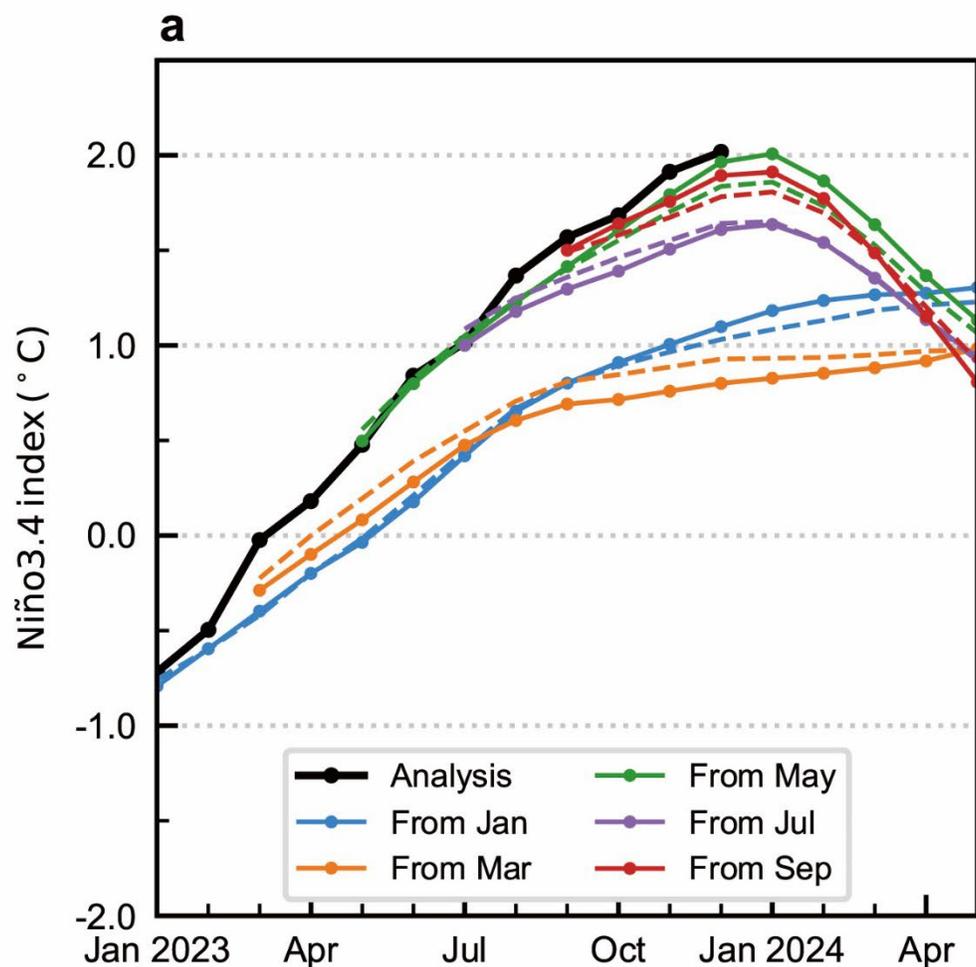
Dynamic models: only one instant state used as initial conditions

Incorporating time sequence information in four dimensions: multi-month time intervals (TIs) in the input predictors as initial conditions

More information during multi-month **TIs** in the input predictors serving as initial conditions, from which the output predictions are derived. This **TI** serves as a new parameter that determines how much information is retained in the input fields, and **also a factor that can be used to improve prediction skills**



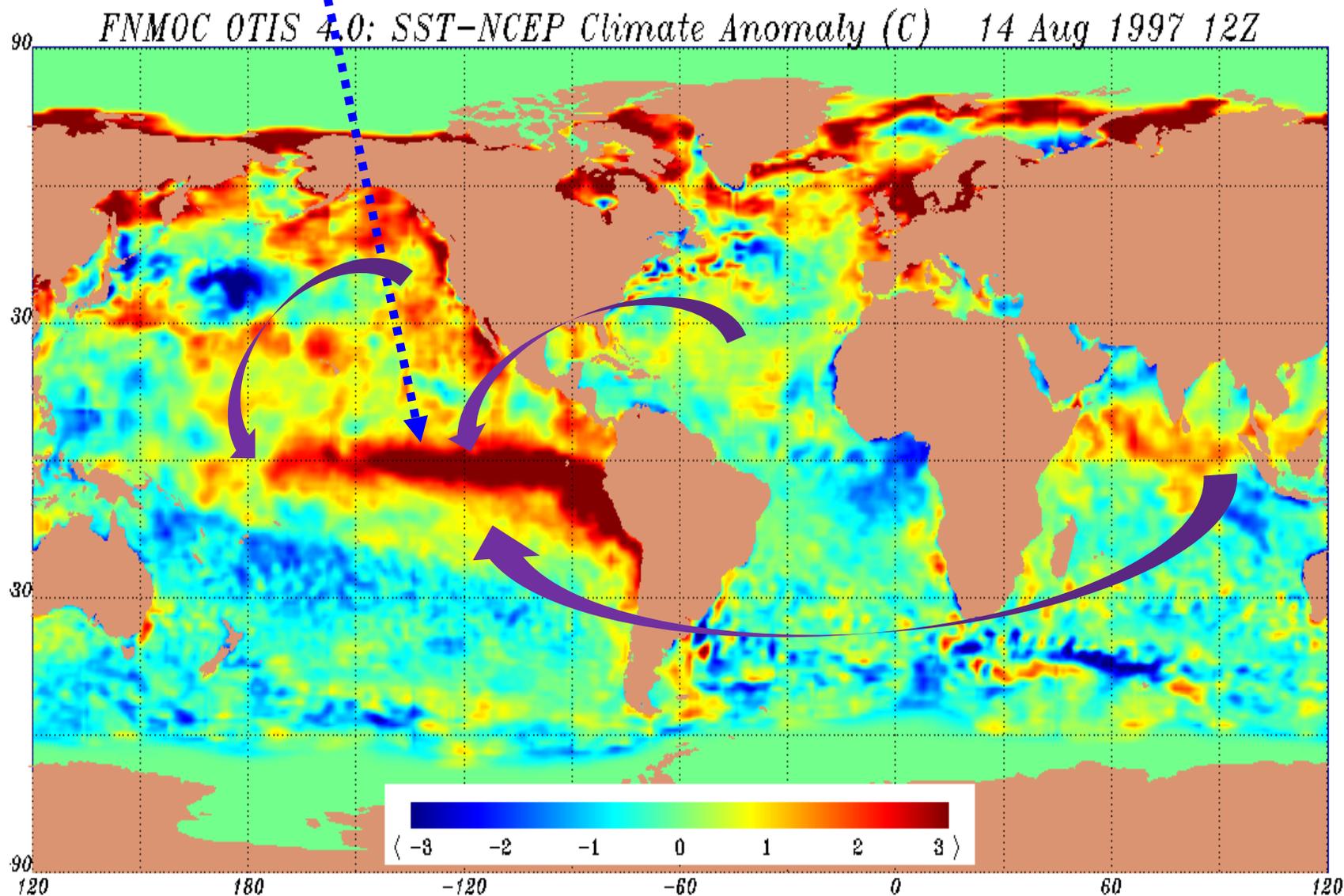
Dynamic models: only one instant state used as initial conditions



(a) GODAS再分析（黑线）和3D-Geoformer（TI=12）分别从2023年1月、3月、5月、7月和9月起报得到的Niño3.4区海温异常演变（彩色线）；其中虚线为3D-Geoformer输入场仅为海温场的结果。（b）使用不同时间序列长度（TI）的变量场作为3D-Geoformer初始场并分别从2023年2月、5月起报得到的Niño3.4区海温异常演变；其中TI=3和TI=18的结果用实线展示。

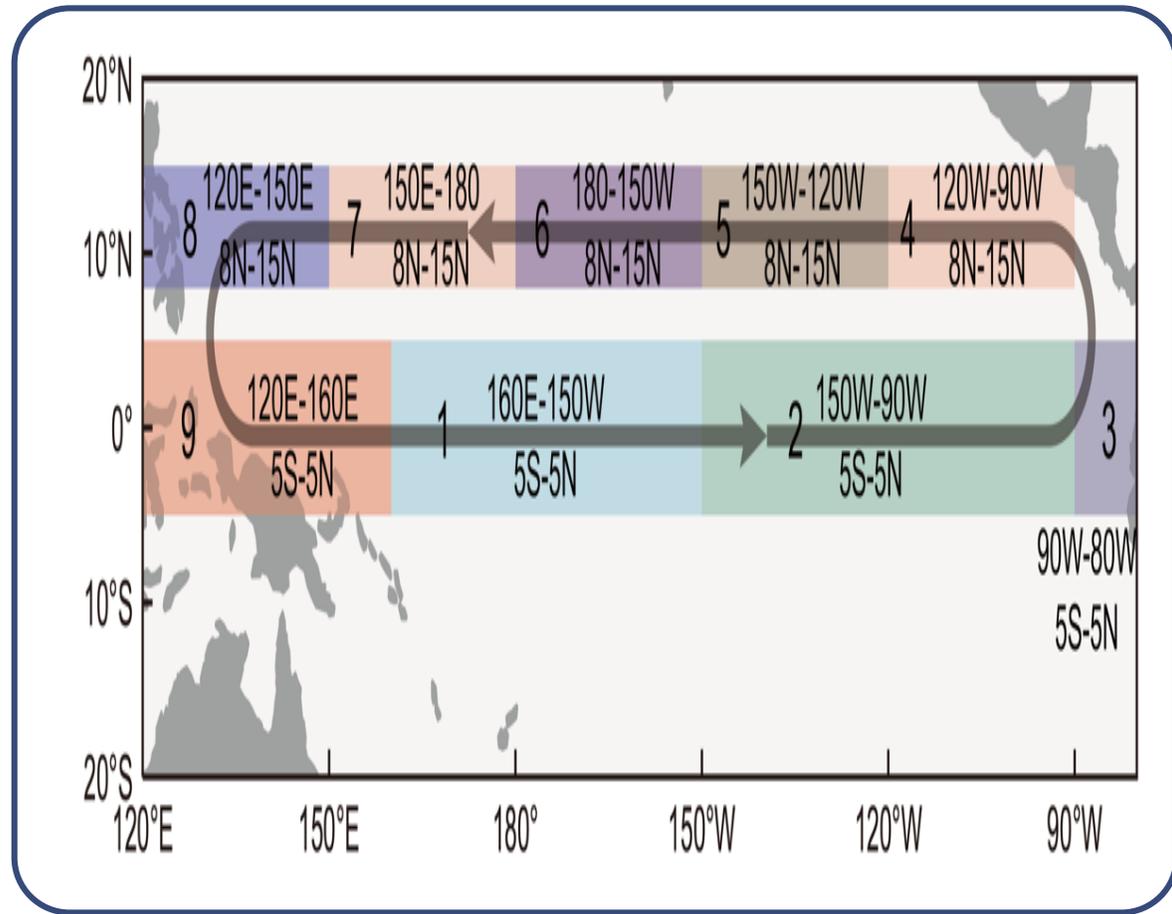
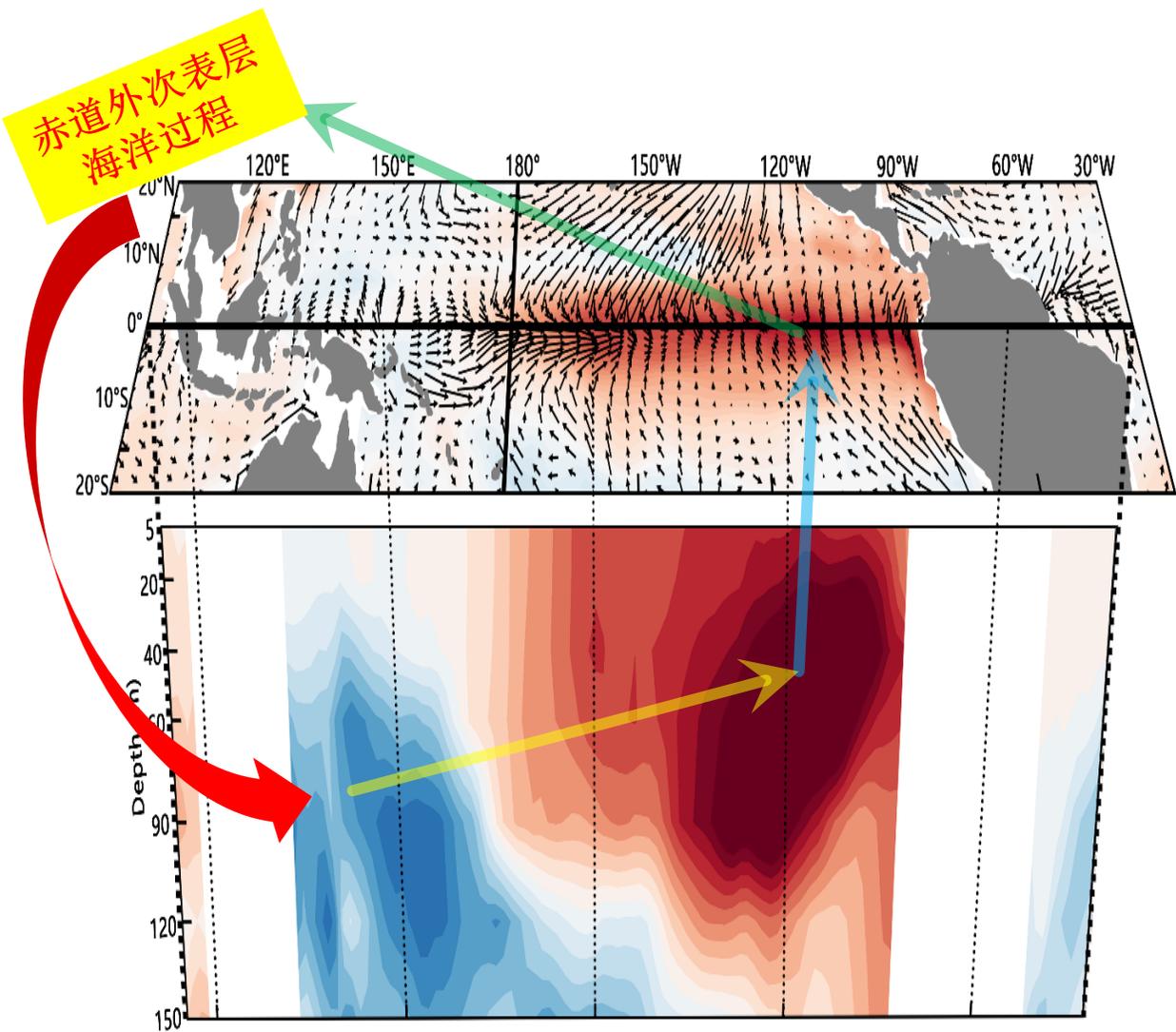
赤道东太平洋海表温度异常可预报性分析

增强可解释性



- ✓ 最能影响 SST 的因素：
变量，空间区域，
时间窗口
- ✓ 敏感性试验
- ✓ Saliency map analyses
- ✓ Explainable AI

从初始场角度追踪引发赤道东太平洋 SST 异常的前期征兆 (precursor)

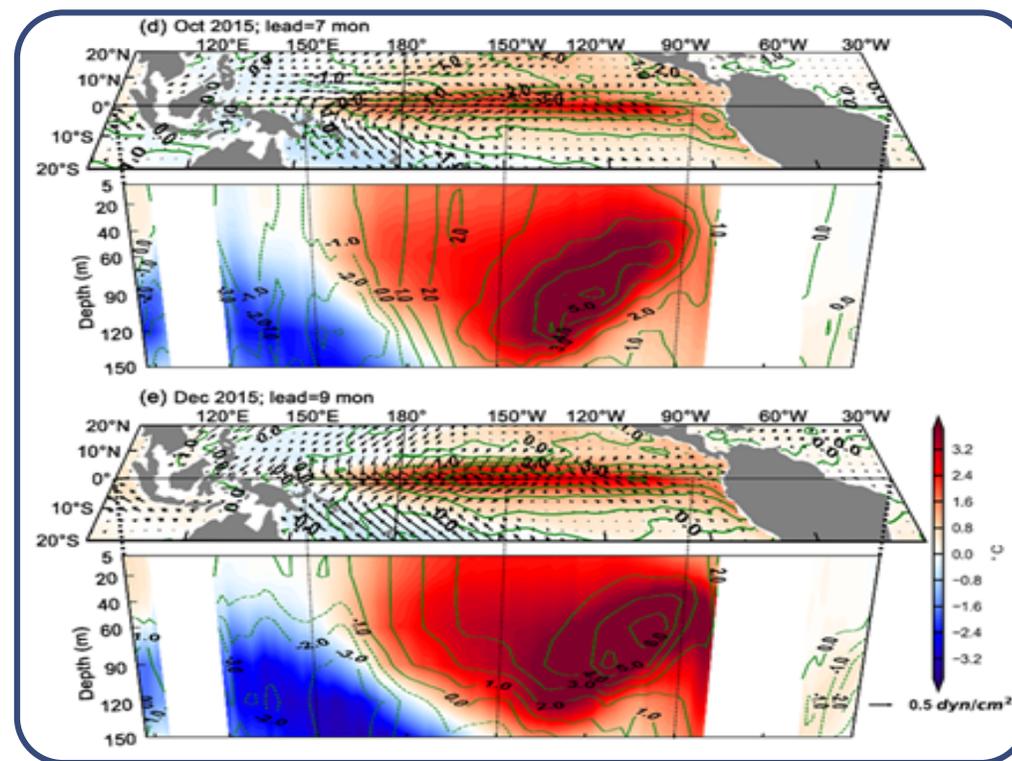
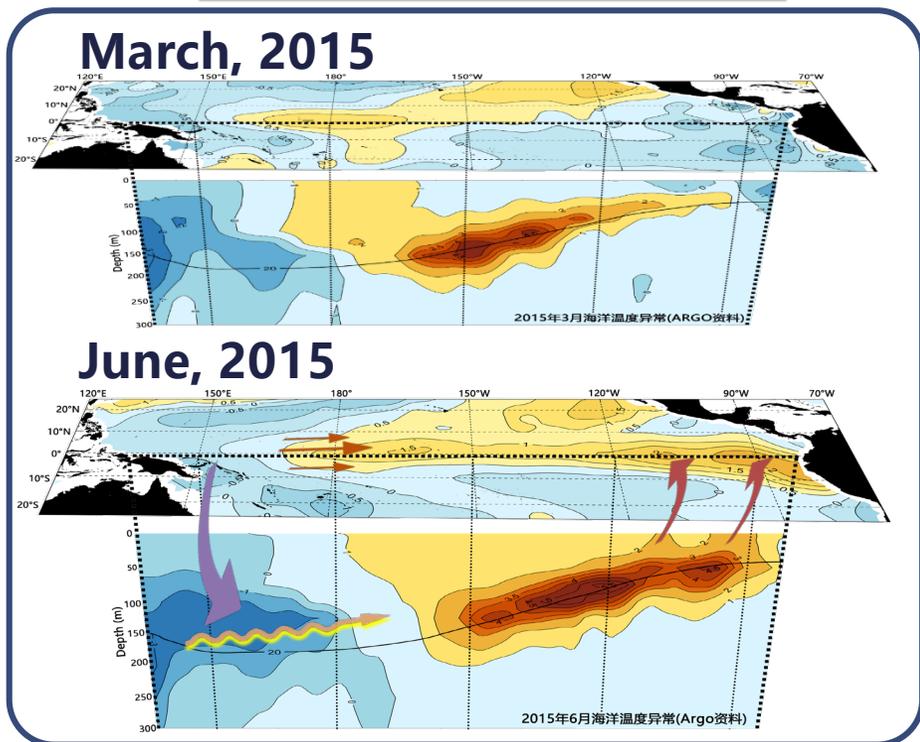


The convenience for conducting **perturbation experiments** from initial condition perspective for ENSO predictability studies

- factors crucial to ENSO prediction skills, including modeling settings (e.g., TIs), sensitive variables & regions;
- its effectiveness in enhancing skills & the mechanisms for good performance (e.g., TIs), **enhancing model explainability**.

多月的多变量做为初条件

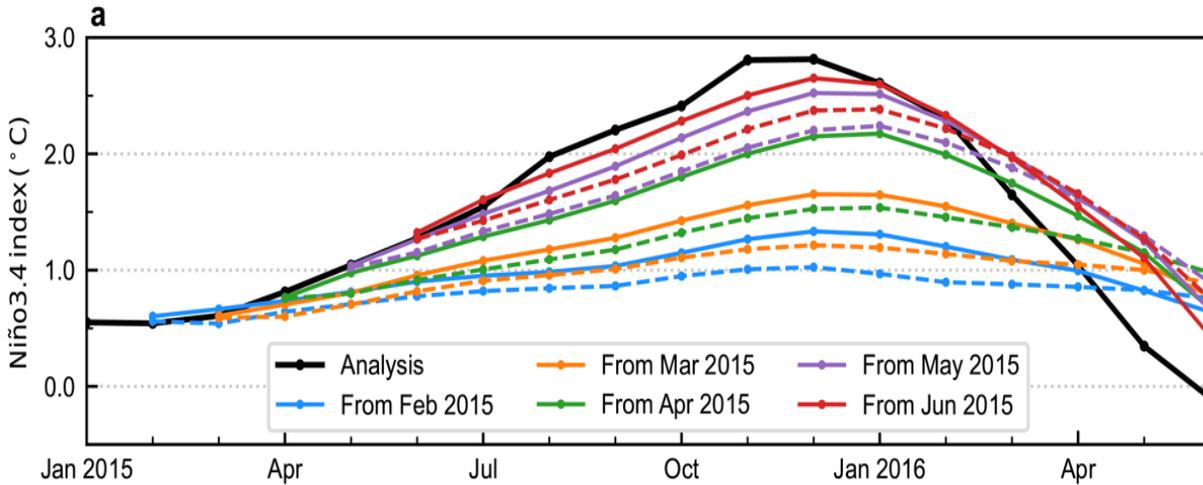
多变量逐月滚动预测



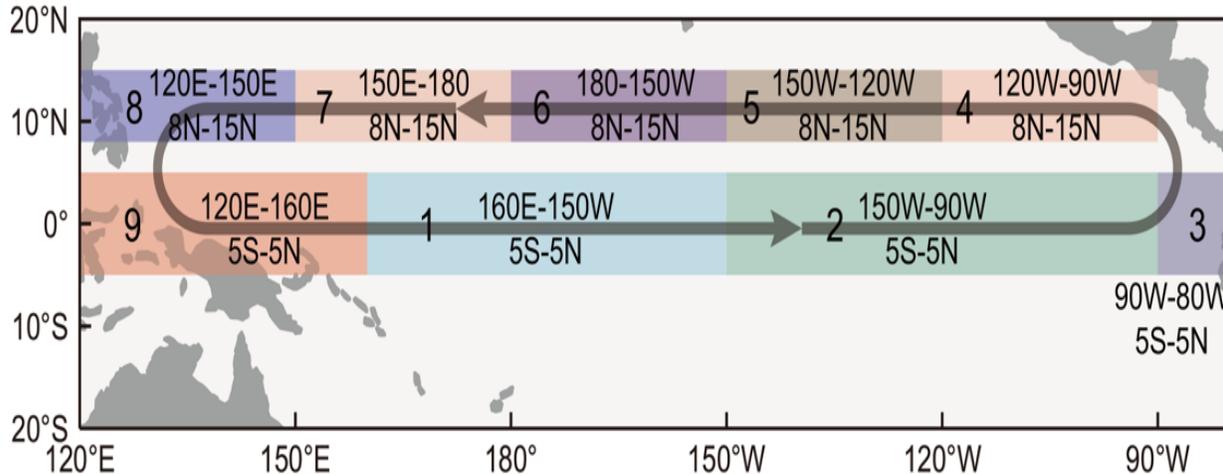
Dynamic models: initial shock & imbalance

Sensitivity tests: processes & interpretability, predictability

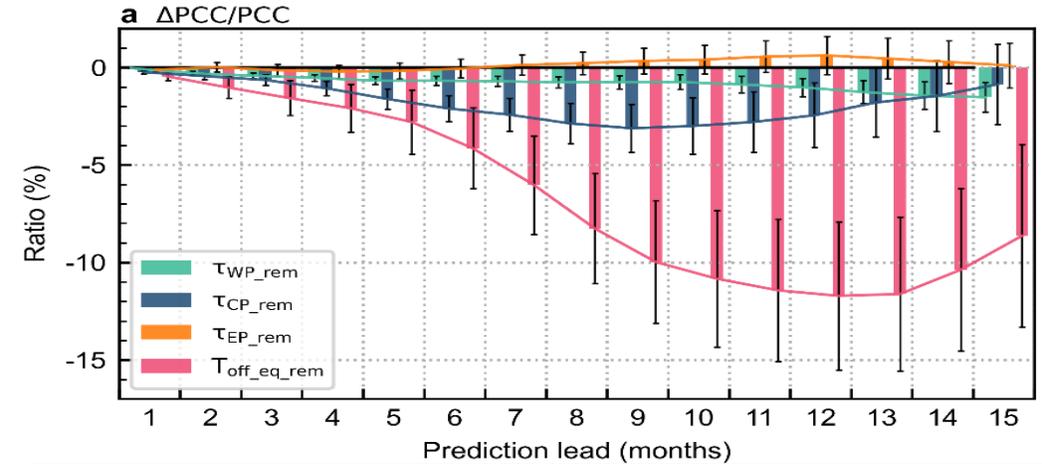
➤ Wind stress **effects** on ENSO predictions



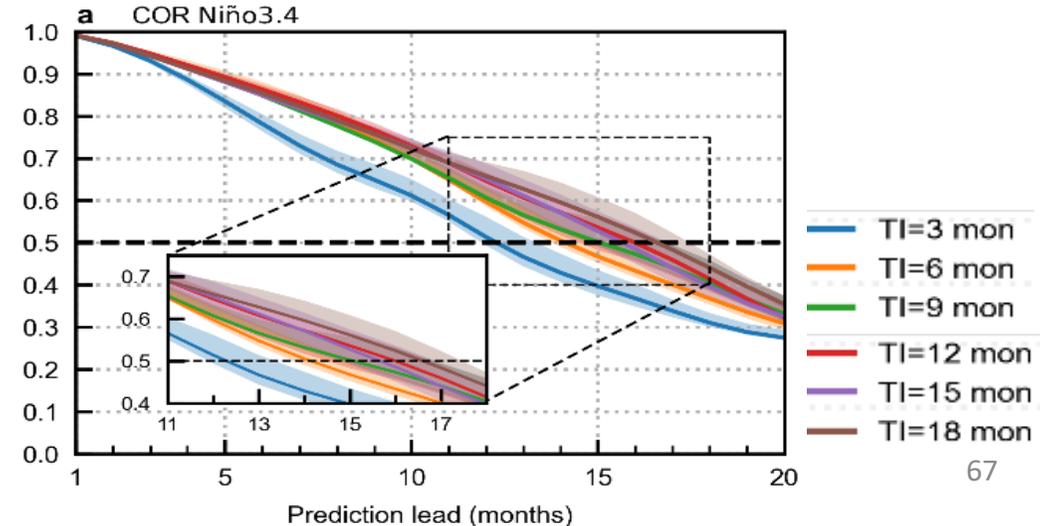
➤ Temperature **precursor propagation** associated with ENSO predictions



➤ Contributions of off-equatorial **temperature effects** to ENSO predictions



➤ Dependence of ENSO predictability on **time intervals (TIs)** taken as multi-variate inputs



基于 AI 的 3D-Geoformer 模型 开展 ENSO 实时预测 和可预报性研究

Science Bulletin xxx (xxxx) xxx



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Perspective

A transformer-based coupled ocean-atmosphere model for ENSO studies

Rong-Hua Zhang^{a,*}, Lu Zhou^{b,c}, Chuan Gao^{b,d,*}, Lingjiang Tao^a

^aSchool of Marine Sciences, Nanjing University of Information Science and Technology, Nanjing 210044, China

^bKey Laboratory of Ocean Observation and Forecasting and Key Laboratory of Ocean Circulation and Waves, Institute of Oceanology, Chinese Academy of Sciences, Qingdao 266071, China

^cUniversity of Chinese Academy of Sciences, Beijing 101408, China

^dLaoshan Laboratory, Qingdao 266237, China

Geophysical Research Letters*

RESEARCH LETTER

10.1029/2023GL104034

Chuan Gao and Lu Zhou contributed equally to this work.

Key Points:

- A transformer-based deep learning model is used for El Niño-Southern Oscillation multivariate prediction in a rolling predictive manner
- The purely data-driven model successfully predicts the 2021 second-year La Niña and turning point of temperature evolution in mid-2021
- Applications of purely data-driven model for process representations and understanding are demonstrated as in dynamical coupled models

Supporting Information:

Supporting Information may be found in the online version of this article.

Geophysical Research Letters*

RESEARCH LETTER

10.1029/2023GL107347

Key Points:

- A deep learning (DL) model is used to conduct El Niño-Southern Oscillation (ENSO) predictability studies for physical interpretability
- DL model experiments are made to identify ENSO-related thermal precursors along a counterclockwise pathway encircling the tropical Pacific
- The existence of upper-ocean thermal anomaly pathways is demonstrated to enhance long-lead ENSO predictability

Supporting Information:

Supporting Information may be found in the online version of this article.

Correspondence to:

R.-H. Zhang,
rzhang@nuist.edu.cn

Citation:

Zhang, R. H., Zhou, L., Gao, C., & Tao, L. (2023). ENSO

A Transformer-Based Deep Learning Model for Successful Predictions of the 2021 Second-Year La Niña Condition

Chuan Gao^{1,2}, Lu Zhou^{1,3}, and Rong-Hua Zhang^{2,3,4}

¹Key Laboratory of Ocean Circulation and Waves, Institute of Oceanology, Center for Ocean Mega-Science, Chinese Academy of Sciences, Qingdao, China, ²Laoshan Laboratory, Qingdao, China, ³University of Chinese Academy of Sciences, Beijing, China, ⁴School of Marine Sciences, Nanjing University of Information Science and Technology, Nanjing, China

Abstract A purely data-driven and transformer-based model with a novel self-attention mechanism (3D-Geoformer) is used to make predictions by adopting a rolling predictive manner similar to that in dynamical coupled models. The 3D-Geoformer yields a successful prediction of the 2021 second-year cooling conditions that followed the 2020 La Niña event, including covarying anomalies of surface wind stress and three-dimensional (3D) upper-ocean temperature, the reoccurrence of negative subsurface temperature anomalies in the eastern equatorial Pacific and a corresponding turning point of sea surface temperature (SST) evolution in mid-2021. The reasons for the successful prediction with interpretability are explored comprehensively by performing sensitivity experiments with modulating effects on SST due to wind and subsurface thermal forcings being separately considered in the input predictors for prediction. A comparison is also conducted with physics-based modeling, illustrating the suitability and effectiveness of 3D-Geoformer as a new platform for El Niño and Southern Oscillation studies.

ENSO-Related Precursor Pathways of Interannual Thermal Anomalies Identified Using a Transformer-Based Deep Learning Model in the Tropical Pacific

Lu Zhou^{1,2} and Rong-Hua Zhang^{2,3,4}

¹Key Laboratory of Ocean Circulation and Waves, Institute of Oceanology, Chinese Academy of Sciences, Qingdao, China, ²University of Chinese Academy of Sciences, Beijing, China, ³School of Marine Sciences, Nanjing University of Information Science and Technology, Nanjing, China, ⁴Laoshan Laboratory, Qingdao, China

Abstract Recent studies have demonstrated great values of deep-learning (DL) methods for improving El Niño-Southern Oscillation (ENSO) predictions. However, the black-box nature of DL makes it challenging to physically interpret mechanisms responsible for successful ENSO predictions. Here, we demonstrate an interpretable method by performing perturbation experiments to predictors and quantifying input-output relationships in predictions by using a transformer-based model; ENSO-related thermal precursors serving as initial conditions during multi-month time intervals (TIs) are identified in the equatorial-northern Pacific, acting to precondition input predictors to provide for long-lead ENSO predictability. Results reveal the existence of upper-ocean temperature anomaly pathways and consistent phase propagations of thermal precursors around the tropical Pacific. It is illustrated that three-dimensional thermal fields and their basinwide evolution during long TIs act to enhance long-lead prediction skills of ENSO. These physically explainable results indicate that neural networks can adequately represent predictable precursors in the input predictors for successful ENSO predictions.

6. 总结与讨论：基于改进的 Transformer 模型和独特设计的时空注意力模块

- 成功构建了基于数据驱动的热带太平洋海洋-大气系统多变量三维（3D）场预测模型，首次对 ENSO 实现了 **单一变量、单点时间序列** 预测到 **多变量、三维立体场** 预测的重要跨越。
- 合理表征海气耦合系统中 Bjerknes 反馈过程及其可持续性，有效提高了热带太平洋多变量、三维立体海温场的准确预测。
- 敏感性试验增强 **可解释性**：验证了模型中基本 ENSO **动力过程** 的合理性，保证其对多变量耦合关系的正确表征，增强了模型预测结果的可信度。
- 具有良好的 **可拓展性** 和方便的开发潜力：允许其稍加修改即可应用于更大区域、更多变量的预测研究，对改进 ENSO 预测和促进人工智能技术在气候变化研究中的应用具有重要的科学意义和应用价值

Science Advances

A self-attention-based neural network for three-dimensional multivariate modeling and its skillful ENSO predictions

LU ZHOU  AND RONG-HUA ZHANG  [Authors Info & Affiliations](#)

相关论文：**Zhou, L., and R.-H. Zhang, 2023: A self-attention based neural network for three-dimensional multivariate modeling and its skillful ENSO predictions. *Science Advances*, 9, eadf2827, <https://doi.org/10.1126/sciadv.adf2827>.**⁶⁹

物理模式和 Transformer 模型用于 ENSO 预测的比较

物理模式: { 动力框架
物理过程参数化
计算实现: 空间离散和时间积分等

Tuning & testing, improving, tuning,

→ 表征 ENSO 特性

做预测: 一个时间层 (即时) 初始场
逐步 (step-by-step) 滚动 (rolling) 向前时间积分

海气耦合: 变量间相互交换实现海气相互作用

观测数据的使用: 资料同化使模式和资料相容;
动力方程容易产生初始 shock 问题

敏感性试验: dynamic adjustment & imbalance issues;
sensitive to perturbations & problematic

Processes-oriented & built-in data

基于数据驱动构建的预报因子与预报量间关系:

$Output = F(input)$

Pre-training

Tuning, testing, improving, tuning,

做预测: { 多个时间层 (如12个月的 input) 场
作为初始场——preconditioning

两种方式: en-to-end 和 rolling stepping

海气耦合: 目前大部分 DL 模式: NO !

观测数据的使用: 直接 inserting; 没有动力方程
而没有动力调整和初始 shock

敏感性试验: convenient way to perform

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- Zhang R.-H., Lu Zhou, Gao, Chuan, 2024: **A transformer-based coupled ocean-atmosphere model for ENSO studies**, *Science Bulletin*, DOI: 10.1016/j.scib.2024.04.048 .
- Zhou Lu, Rong-Hua Zhang, Chuan Gao, 2024: **ENSO-related precursor pathways of interannual thermal anomalies identified using a transformer-based deep learning model in the tropical Pacific**, *Geophys. Res. Lett.*, 51, e2023GL107347.
- Gao, Chuan, Lu Zhou, and Rong-Hua Zhang, 2023: **A transformer-based deep learning model for successful predictions of the 2021 second-year La Niña condition**, *Geophys. Res. Lett.*, in press. doi: 10.1029/2023GL104034
- Zhu, Yuchao, Rong-Hua Zhang, 2023: A deep learning-based U-Net model for ENSO-related precipitation responses to sea surface temperature anomalies over the tropical Pacific, *Atmospheric Oceanic Science Letters*, in press. <https://doi.org/10.1016/j.aosl.2023.100351>
- Zhou, Lu and Rong-Hua Zhang, 2023: **A self-attention-based neural network for three-dimensional multivariate modeling and its skillful ENSO predictions**. *Science Advances*, 9(10), [DOI: 10.1126/sciadv.adf2827](https://doi.org/10.1126/sciadv.adf2827)
- Zhou, Lu, Chuan Gao, Rong-Hua Zhang, 2023: A spatiotemporal three-dimensional CNN model for ENSO predictions: A test case for the 2020-2021 La Nina conditions, *Atmospheric Oceanic Science Letters*, in press. doi: <https://doi.org/10.1016/j.aosl.2023.100330>.
- Zhu, Yuchao, Rong-Hua Zhang, James N Moum, Fan Wang, Xiaofeng Li, Delei Li, 2022: **Physics-informed Deep Learning Parameterization of Ocean Vertical Mixing Improves Climate Simulations**, *National Science Review*, 9(8), nwac044, <https://doi.org/10.1093/nsr/nwac044>



Thank You!

融合人工智能海表风场和海洋动力过程的 混合型海气耦合模式及其对 ENSO 的模拟

张荣华 杜双盈 周路 高川
南京信息工程大学海洋科学学院

首次成功实现了神经网络与基于物理过程的海气耦合模式间有效融合，为AI模型与动力模式间的混合建模提供了一种示范框架。

- 利用U-Net模型表征热带太平洋SSTA与风应力异常之间的关系，并使用训练好的U-Net模型代替 IOCAS ICM 的大气模块中基于SVD分析构建的统计模型，形成ICM-UNet。
- 利用U-Net模型得到的风应力异常驱动ICM的海洋模块，所得结果可以模拟出典型的El Niño事件，再次证实了神经网络与基于物理过程模式融合的可行性。
- ICM-UNet得到的模式结果能够形成并维持稳定的年际振荡，表明神经网络可以作为用于模拟和分析ENSO事件的动力模式的一部分，

相关论文： Du, S. Y., and R.-H. Zhang, 2024: U-Net models for representing wind stress anomalies over the tropical Pacific and their integrations with an intermediate coupled model for ENSO studies. *Advance of Atmospheric Sciences*, <https://doi.org/10.1007/s00376-023-3179-2>

创新性及阶段性成果

- ✓ 人工智能（AI）方法应用于地球系统物理过程参数化及气候模拟的改进

- ✓ 率先成功构建了基于数据驱动的热带太平洋海洋-大气系统多变量三维（3D）场预测模型，首次对ENSO实现了**单一变量、单点时间序列**预测到**多变量、三维立体场**预测的重要跨越。



Article Navigation

JOURNAL ARTICLE

Physics-informed deep-learning parameterization of ocean vertical mixing improves climate simulations

Yuchao Zhu, Rong-Hua Zhang , James N Moum, Fan Wang, Xiaofeng Li, Delei Li

朱聿超, 张荣华* 等 (2022)

基于自注意力神经网络模拟海气**多变量三维场**
耦合系统及其对 **ENSO** 跨年度的成功预测

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A self-attention-based neural network for three-dimensional multivariate modeling and its skillful ENSO predictions

LU ZHOU AND RONG-HUA ZHANG [Authors Info & Affiliations](#)

周路 张荣华* (2023年3月)

A Purely Data-driven **Transformer**-Based Coupled Ocean-Atmosphere Model for ENSO Research

张荣华 周路 高川
南京信息工程大学海洋科学学院等

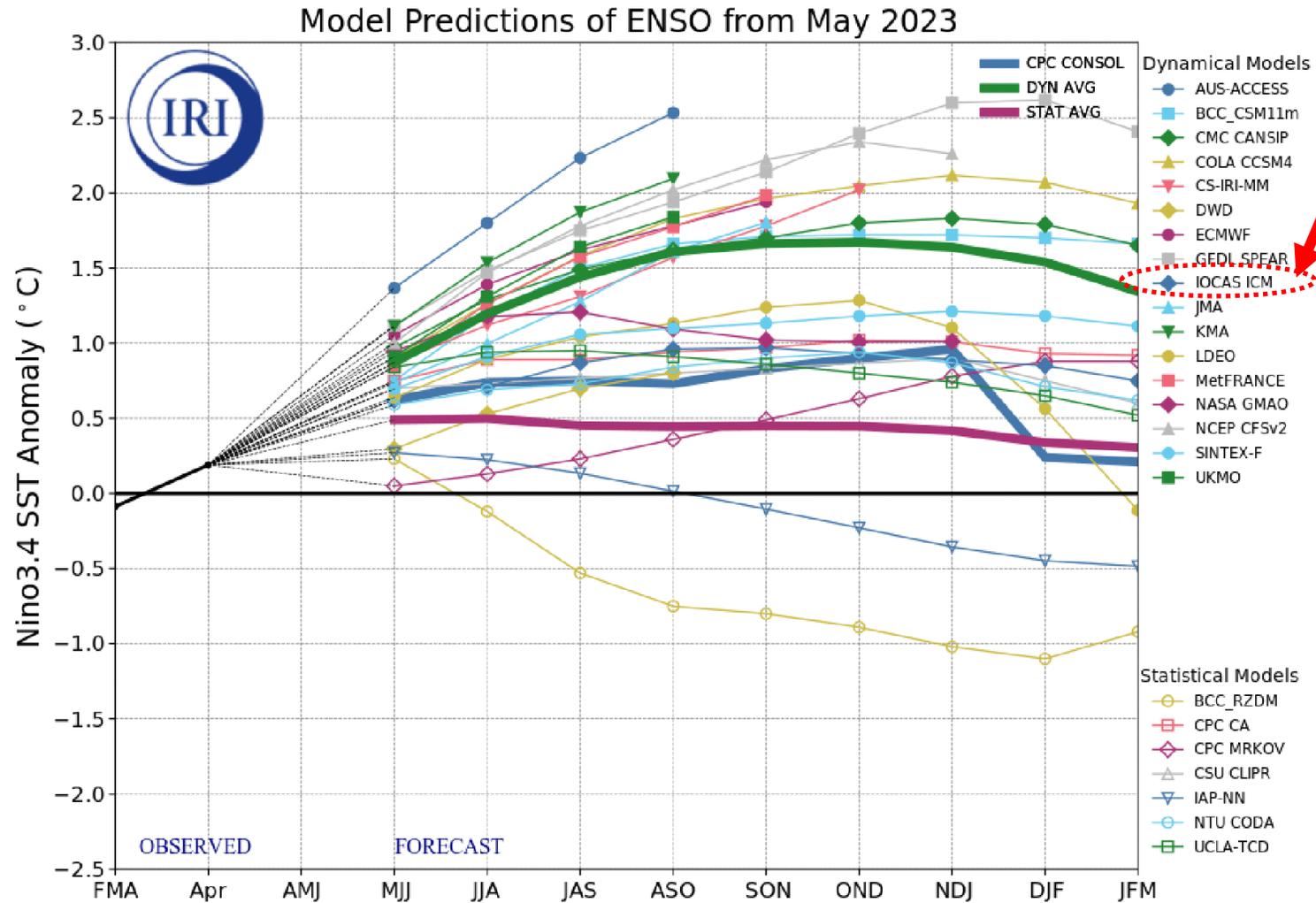
ScienceAdvances

A self-attention-based neural network for three-dimensional multivariate modeling and its skillful ENSO predictions

[LU ZHOU](#)  AND [RONG-HUA ZHANG](#)  [Authors Info & Affiliations](#)

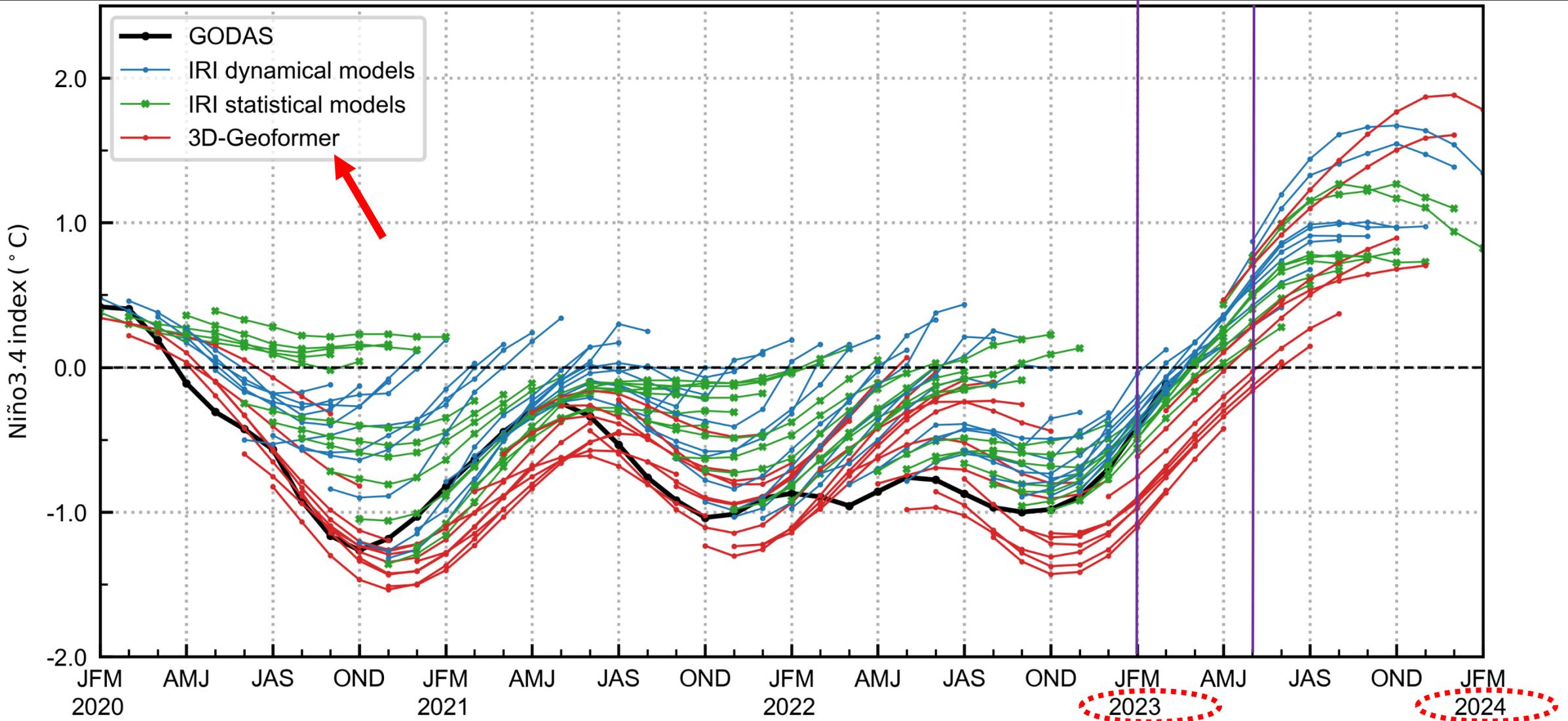
基于自注意力神经网络模拟海气多变量**三维场耦合系统**及其对 ENSO
跨年度的成功预测

4.6 Real-time predictions: IRI collections, including IOCAS ICM (Intermediate coupled model)



- Predictions of SST anomalies for the Niño 3.4 region. Figure updated by International Research Institute (IRI) for Climate and Society.

4.6 Real-time predictions: 3D-Geoformer



ORAS5 reanalysis (black lines) and predicted (colored lines) Niño3.4 SST anomalies during 2020-2023. The blue and green lines indicate the predictions made by dynamical and statistical models from the IRI collection, and the red lines indicate the predictions made using 3D-Geoformer.

特色、优势和应用： a new modeling tool

✓ Its ability to adequately represent the ocean-atmosphere coupling **within the DL-based modeling context: monthly coupling in a rolling way**

✓ Retrospective hindcast experiments: surpassing other conventional statistical and dynamic models

✓ Incorporating time sequence information in four dimensions: **multi-month time intervals (TIs) in the input predictors serving as initial conditions**

More information during multi-month **TIs** in the input predictors serving as initial conditions, from which the output predictions are derived. This **TI** serves as a new parameter that determines how much information is retained in the input fields, and also a factor that can be used to improve prediction skills

✓ **The convenience for conducting perturbation experiments from initial condition perspective for ENSO predictability studies.**

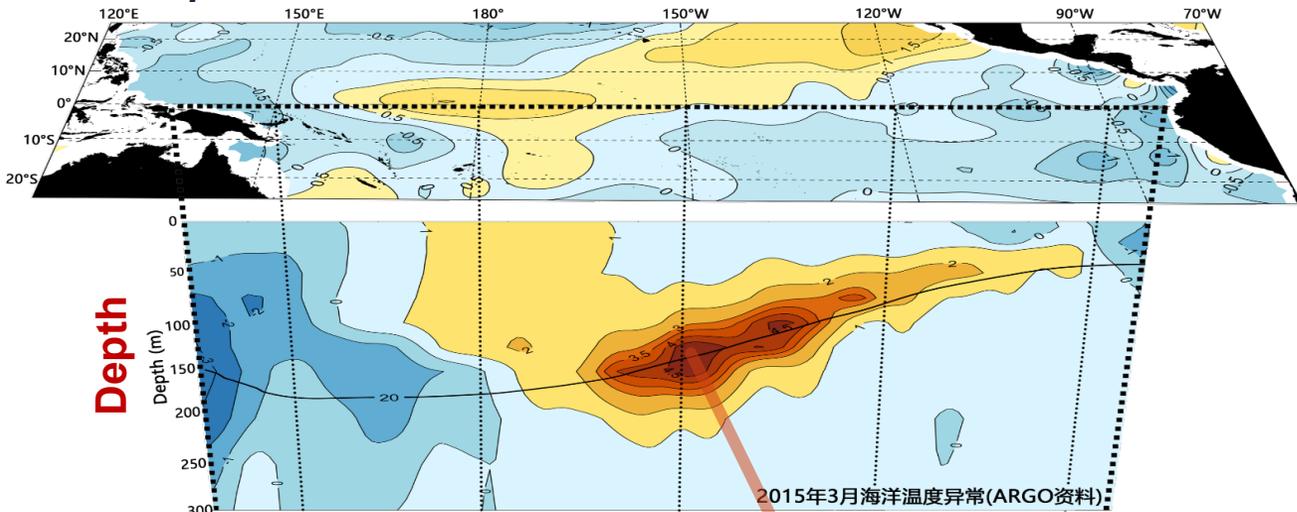
understanding factors crucial to ENSO prediction skills, including modeling settings (e.g., TIs), sensitive variables, and regions; its effectiveness in enhancing skills & the mechanisms for good performance (e. g., TIs), thereby enhancing model explainability₇₉

1. 研究背景

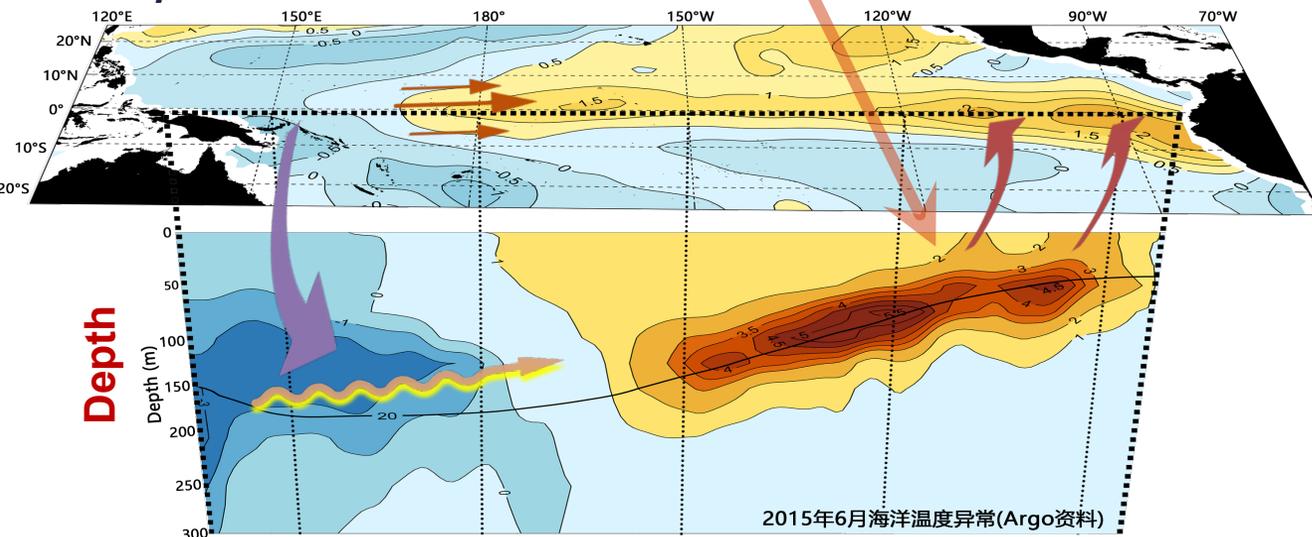
ENSO 预测的物理基础：多变量三维场时空演变和相互作用

时空演变和海气相互作用

March, 2015



June, 2015

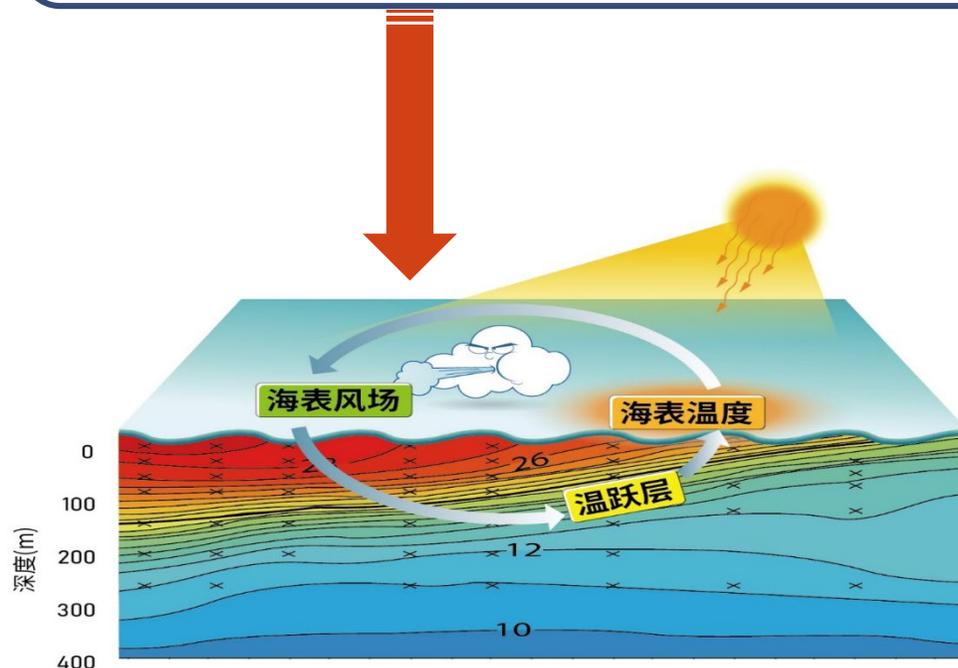


时间尺度：季节到年际

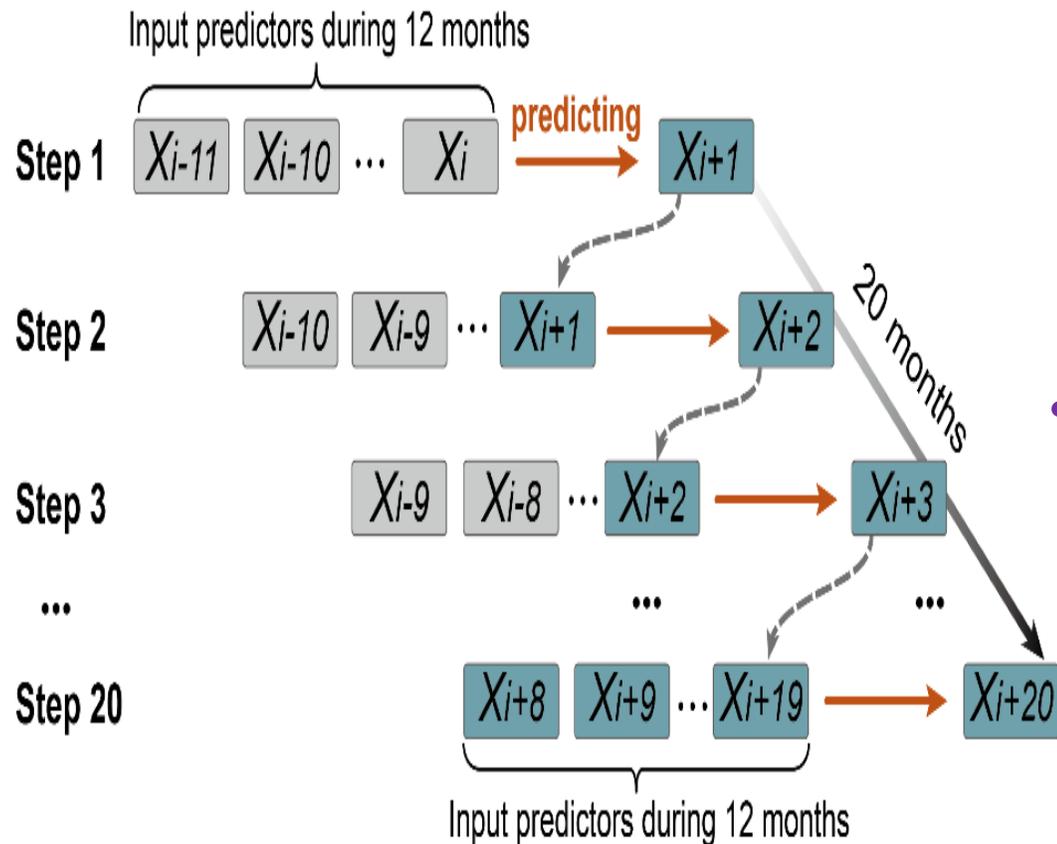
空间尺度：整个热带太平洋；海气异常协同变化

ENSO 有明确的过程和机制：次表层异常信号显现出传播性和持续性；激发远程响应、反馈和海气相互作用；使得海气异常产生后可在季节到年际时间尺度上得以维持。这种次表层中年际尺度的“记忆”能力为 ENSO 预测提供了物理基础

多变量相互作用提供了 ENSO 可预测性



The convenience for conducting perturbation tests from initial condition perspective for ENSO predictability studies.



- demonstrate its effectiveness in enhancing skills
- understand factors crucial to ENSO prediction skills:
 - modeling settings (e.g., TIs)
 - sensitive variables
 - sensitive regions
- illustrate the mechanisms for good performance (e. g., TIs), thereby enhancing model explainability.