A Unified Time-Dependent Theory of Tropical Cyclone Intensification and Its applications: Current Status and Future Directions

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Outline

- **Classic views on tropical cyclone (TC) intensification**
- **Early efforts toward time-dependent theories**
- **A unified time-dependent theory of TC intensification**
- **Applications:**

  Quantifying environmental effects on TC intensity change

  Prediction of TC intensity

- **Future directions**

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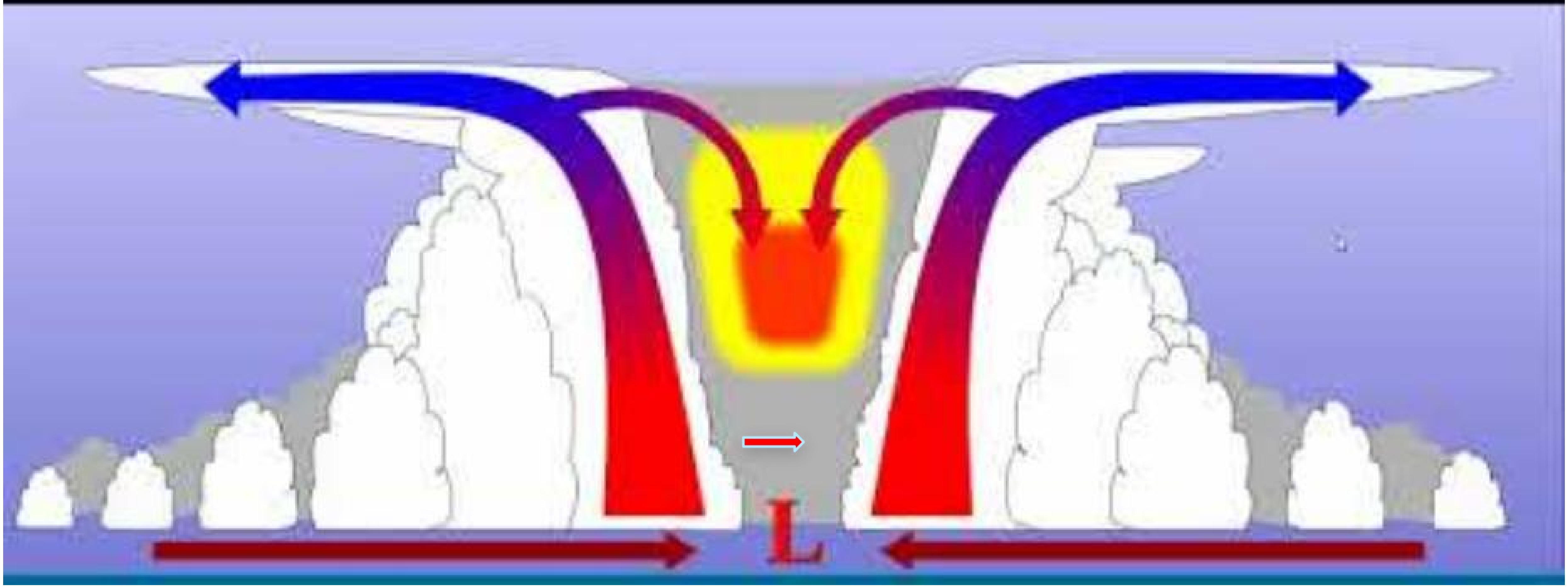
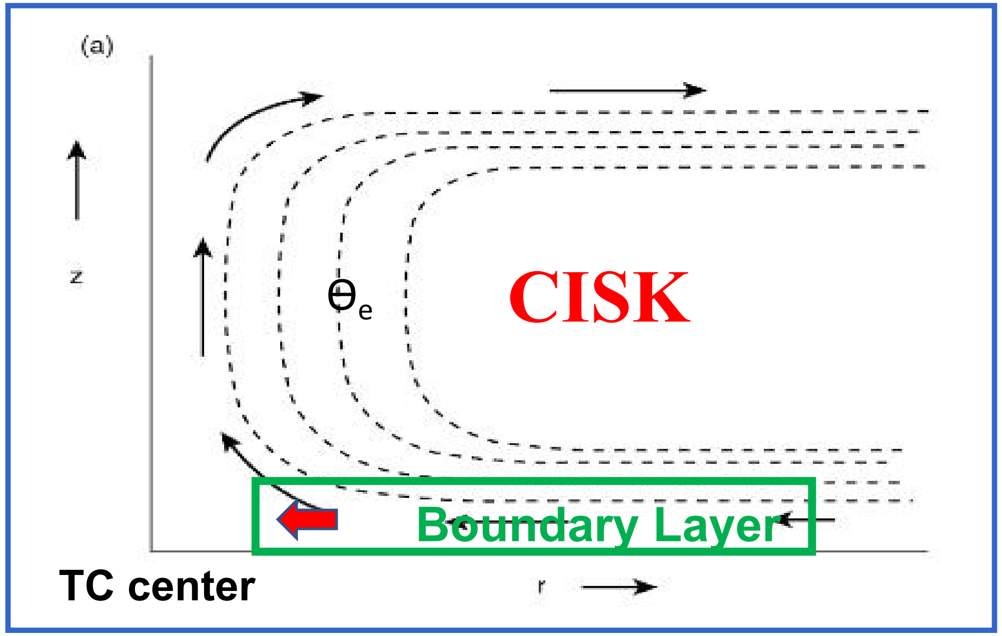
Classic views on TC intensification

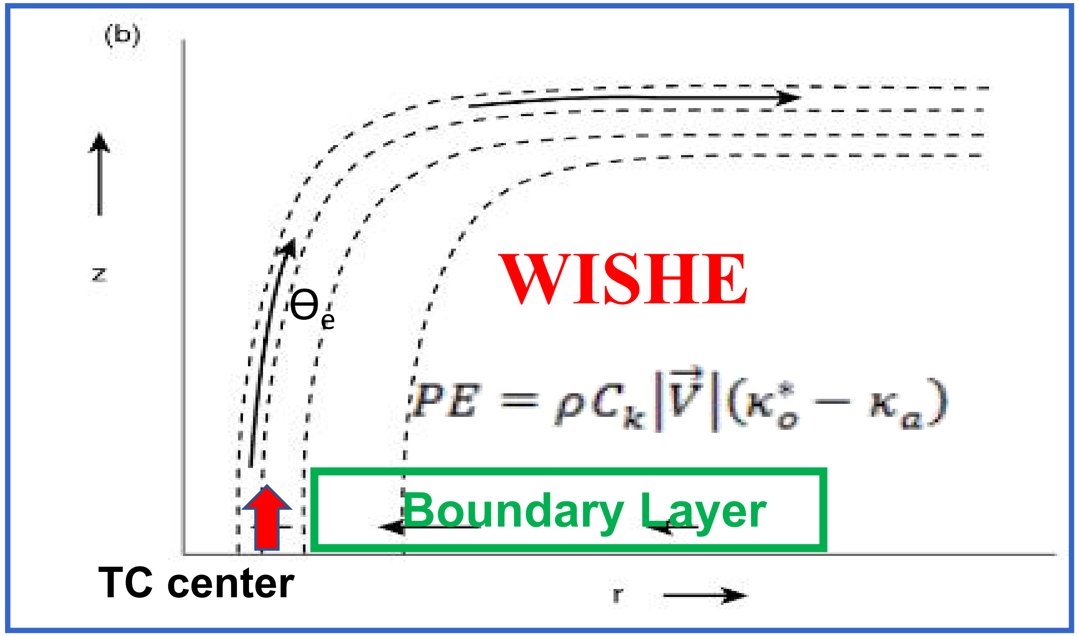


1964: CISK 1982:Balanced dynamics 1986: WISHE

All are qualitative descriptions – Emphasize a certain positive feedback process

Classic views on TC intensification





Strong moist convection → Latent heating release → Lower pressure system → Ekman pumping & moisture convergence → Strong moist convection

Surface heat flux under the eyewall → Bring higher Θ_e into the eyewall → Enhance radial entropy gradient → Tangential wind increases → Surface heat flux under the eyewall

Classic views on TC intensification

Balanced vortex dynamics

For an axisymmetric TC

$$\frac{\partial V_{max}}{\partial t} = -u_m \xi_{a,rm} - w_{rm}\frac{\partial V_{max}}{\partial z} + F_{vrm}$$

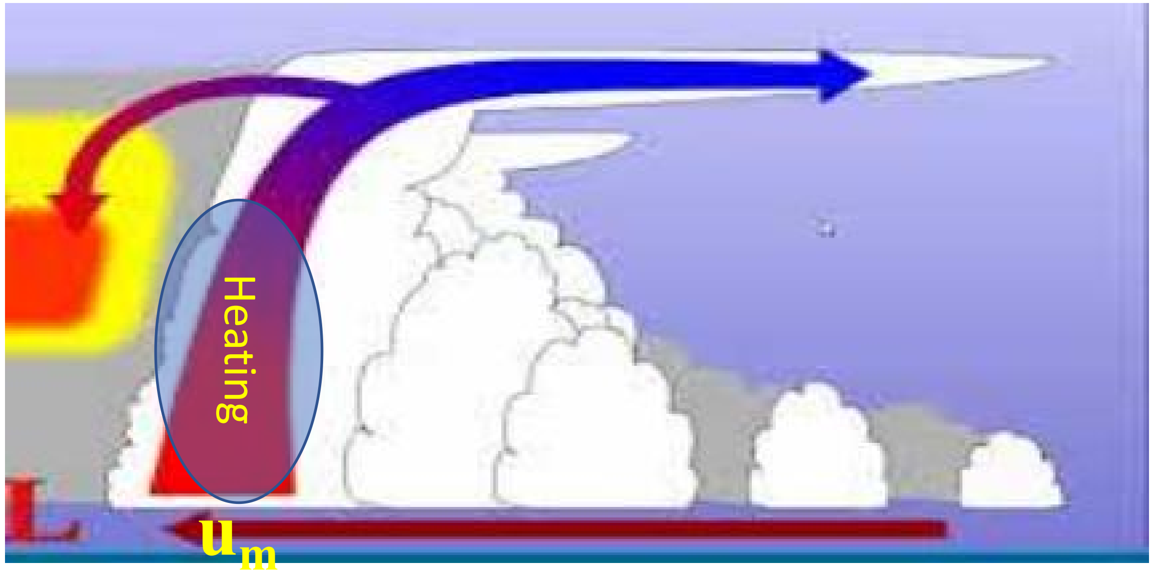
Intensification potential

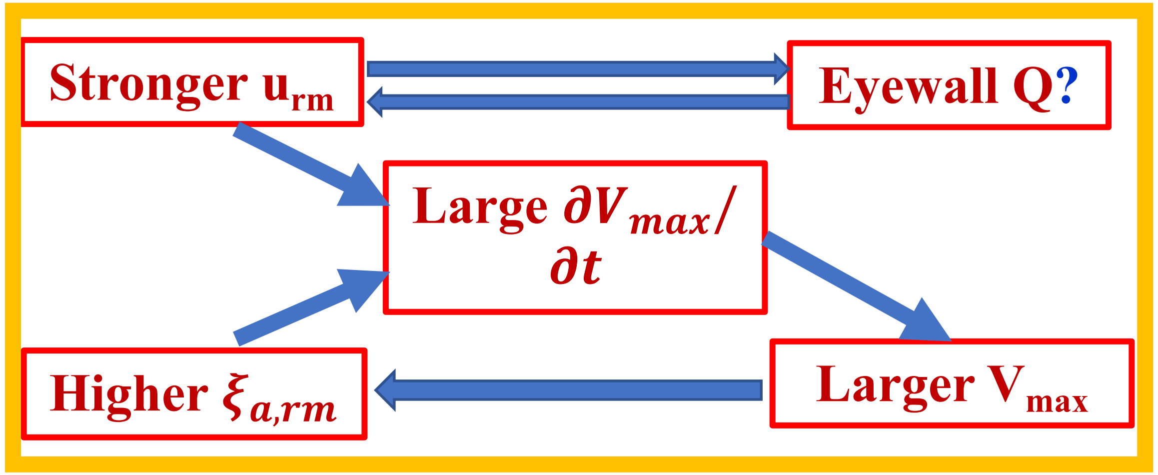
$$\frac{\partial V_{max}}{\partial t} \infty - u_{rm} \xi_{a,rm} - w_{rm}\frac{\partial V_{max}}{\partial z}$$

Frictional weakening

$$\frac{\partial V_{max}}{\partial t} \infty - \frac{C_D}{H} V_{max}^2$$

Schubert & Willoughby(1982)





Classic views on TC intensification

- **Classic views:** Qualitative descriptions of certain positive feedback processes (CISK, WISHE, balanced dynamics)

- **New efforts:** To quantify TC intensification rate by developing physically/dynamically based time-dependent theories (equations)

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- **Significance:**

– A theoretical basis for understanding climate change impact on TC intensification, similar to MPI theory on TC intensity.

– Potential applications to TC intensity forecasting.

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- Future directions

Early efforts toward time-dependent theories

- **Dynamically based time-dependent theory (Emanuel 2012)**

Slab boundary layer entropy & momentum budget equations

+

Moist neutral eyewall convection (ascent)

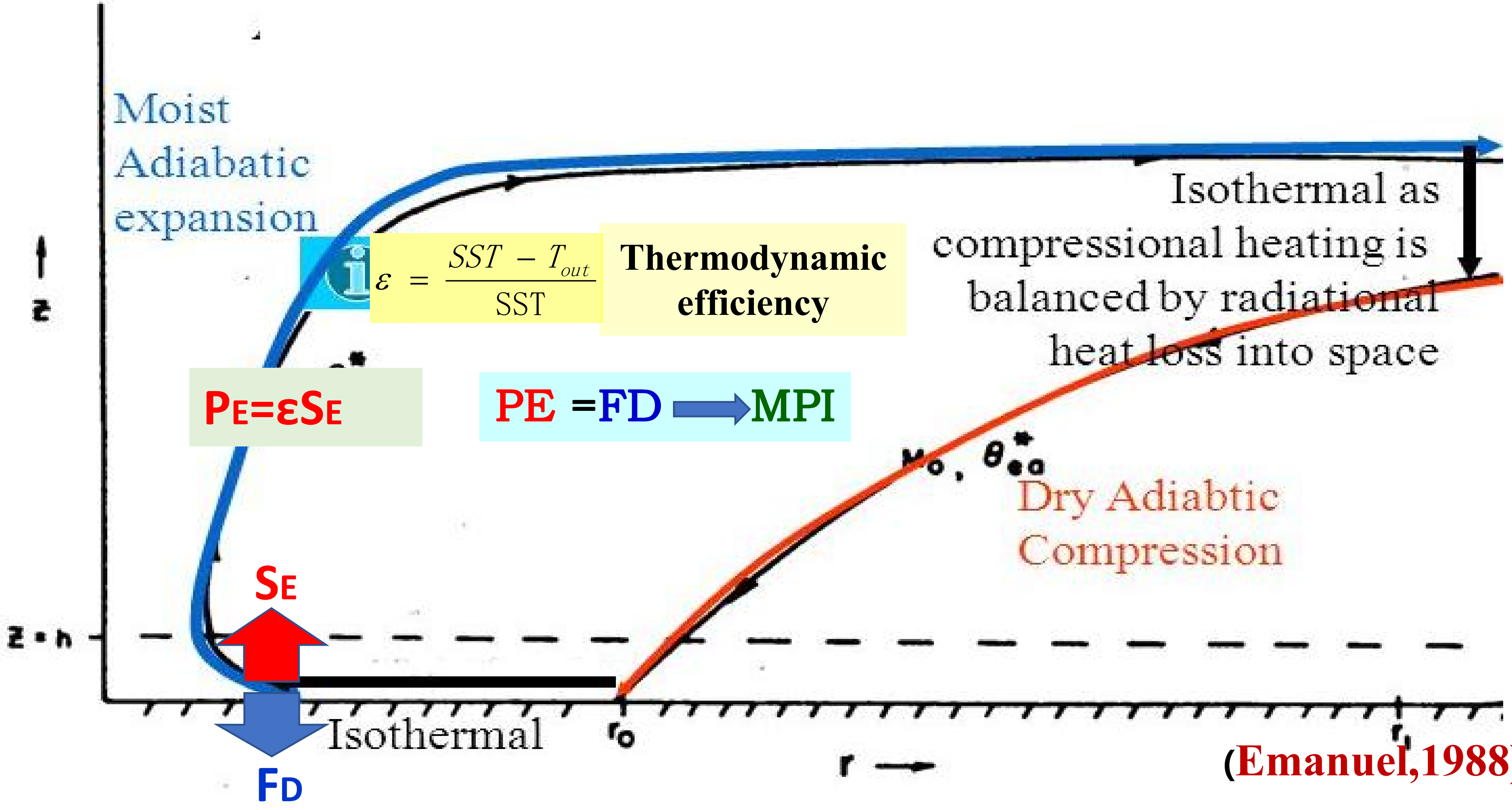
- **Energetically based time-dependent theory (Ozawa & Shimokawa 2015)**

Unsteady Carnot heat engine

+

Bulk energy conversion rate

Carnot Heat Engine and TC MPI theory

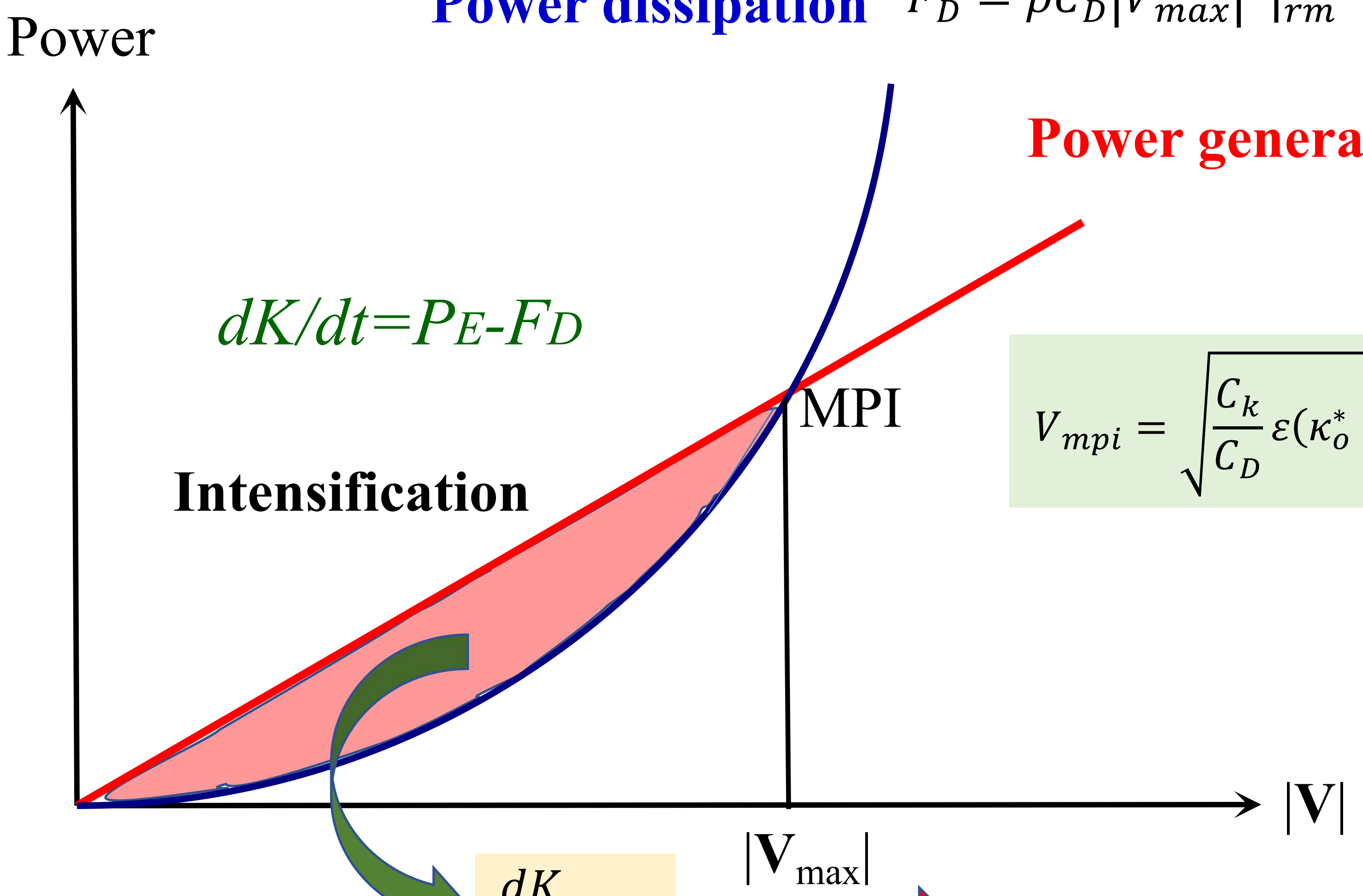


(Emanuel,1988)

Unsteady Carnot Heat Engine and TC Intensification

Power dissipation $F_D = \rho C_D |\overrightarrow{V_{max}}|^3 |_{rm}$

Power generation $P_E = \rho \epsilon C_k |\overrightarrow{V_{max}}| (\kappa_o^* - \kappa_a)|_{rm}$



$$V_{mpi} = \sqrt{\frac{C_k}{C_D} \varepsilon (\kappa_o^* - \kappa_a)|_{rm}}$$

E-MPI

$$\frac{dK}{dt} > 0$$

TC intensification

Wang (2012, 2015)

Energetically based time-dependent theory

$$P_E = \int \varepsilon C_k \rho |\vec{V}| (\kappa_o^* - \kappa_a) r dr d\lambda$$

$$\varepsilon = \frac{SST - T_{out}}{\mathrm{SST}}$$ Thermodynamic efficiency

$$F_D = \int C_D \rho |\vec{V}|^3 r dr d\lambda$$

$$EGR = \mu P_E - F_D = \mu \rho \epsilon C_k |\vec{V}| (\kappa_o^* - \kappa_a)|_{rm} - \rho C_D |\vec{V}|^3 |_{rm}$$

Ozawa & Shimokawa (2015) assumed **μ=70%** of heat energy is converted to inner-core mechanical energy

$$EGR = \rho H \frac{d}{dt}\left(\frac{1}{2} V_{max}^2\right) \rightarrow \frac{dV_{max}}{d\tau} = \frac{C_D}{H}\left(\mu V_{mpi}^2 - V_{max}^2\right)$$

$$V_{mpi} = \sqrt{\frac{C_k}{C_D} \varepsilon (\kappa_o^* - \kappa_a)|_{rm}}$$

Ozawa & Shimokawa (2015)

Dynamically based time-dependent theory

Emanuel's time-dependent theory

Starting from momentum and entropy budget equations in angular momentum coordinates

$[\, M = r(V + \frac{1}{2} f\mathrm{r}) \,]$

$$\boxed{\frac{\partial s_b}{\partial \tau} + \dot{M}\frac{\partial s_b}{\partial M} = g\frac{\partial F}{\partial P} + D, \qquad \dot{M} = gr\frac{\partial \tau_\theta}{\partial P},}$$

Integrating both vertically through the boundary layer

$$\Delta p_b \frac{\partial s_b}{\partial \tau} + gr\tau_{\theta s}\frac{\partial s_b}{\partial M} = gF_s + \overline{D},$$

Using bulk scheme for surface boundary condition

$$F_s = \frac{C_k \rho |\mathbf{V}|(k_0^* - k_b)}{T_s} \cong C_k \rho |\mathbf{V}|(s_0^* - s_b) \qquad \tau_{\theta s} = -C_D \rho |\mathbf{V}| V,$$

An equation for boundary layer entropy budget

$$h\frac{\partial s_b}{\partial \tau} - C_D r |\mathbf{V}| V \frac{\partial s_b}{\partial M} = C_k |\mathbf{V}|(s_0^* - s_b)$$

Emanuel (2012)

Dynamically based time-dependent theory

Emanuel's time-dependent theory

Emanuel (2012) made the following assumptions:

1) A TC is assumed to be axisymmetric and in thermal wind balance above the boundary layer;
2) The radius of maximum wind is a material surface, and thus the angular momentum ($V_{max}*R_m$) is nearly a constant;
3) The absolute angular momentum (*M*) surface and the saturation entropy (*s**) surface are nearly congruent in eyewall ascent, namely the eyewall ascent is moist neutral.

$$\frac{\partial V_{max}}{\partial \tau} \cong \frac{C_k}{2h}\left(V_{mpi}^2 - V_{max}^2\right) \quad \Longleftrightarrow \quad \frac{dV_{max}}{d\tau} = \frac{C_D}{H}\left(\mu V_{mpi}^2 - V_{max}^2\right)$$

$$V_{mpi}^2 = \frac{C_k}{C_D}\left(\frac{1}{2}\frac{C_k}{C_D}\right)^{(C_k/C_D)/[2-(C_k/C_D)]}(T_b - T_t)(s_0 - s_e^*)$$

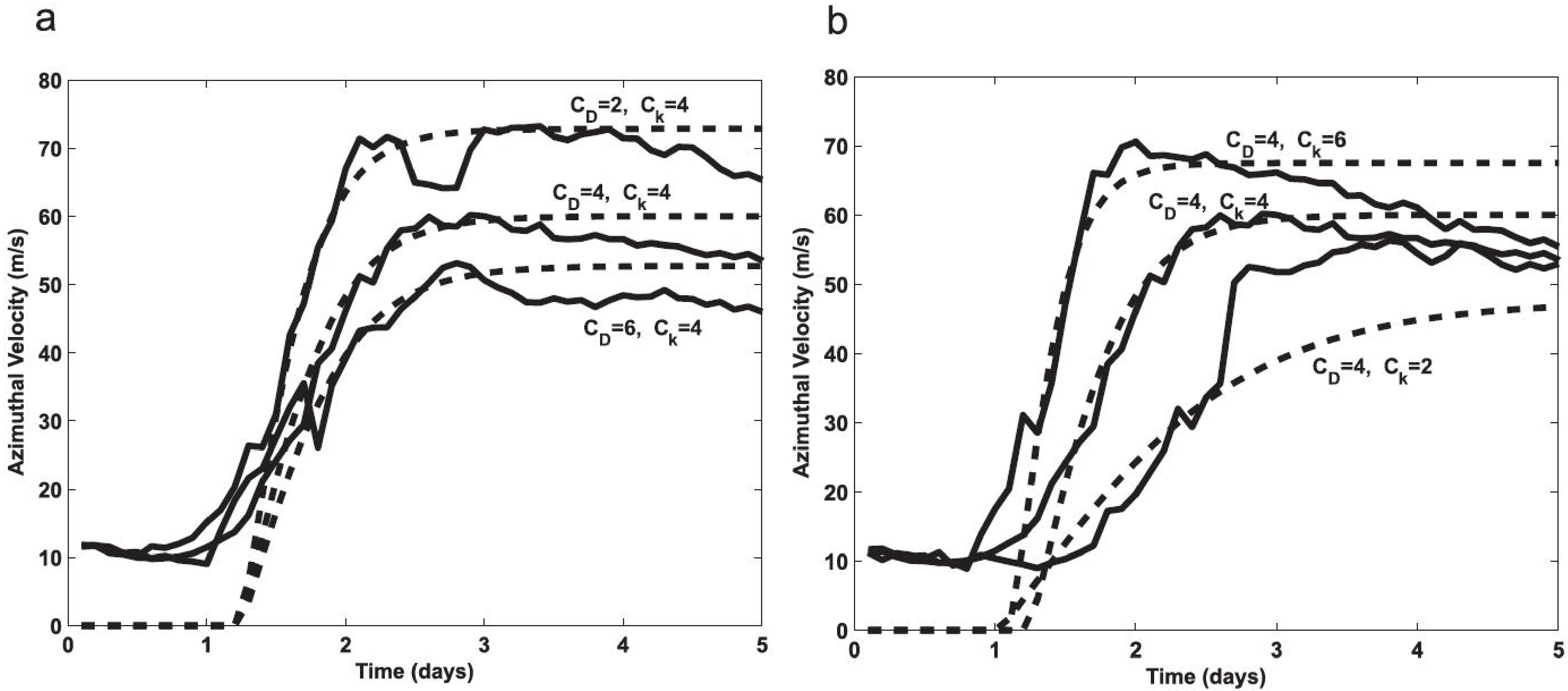
Emanuel (2012)

Dynamically based time-dependent theory

Emanuel's time-dependent IR equation

$$\frac{\partial V_{max}}{\partial \tau} = \frac{C_k}{2h}\left(V_{mpi}^2 - V_{max}^2\right)$$

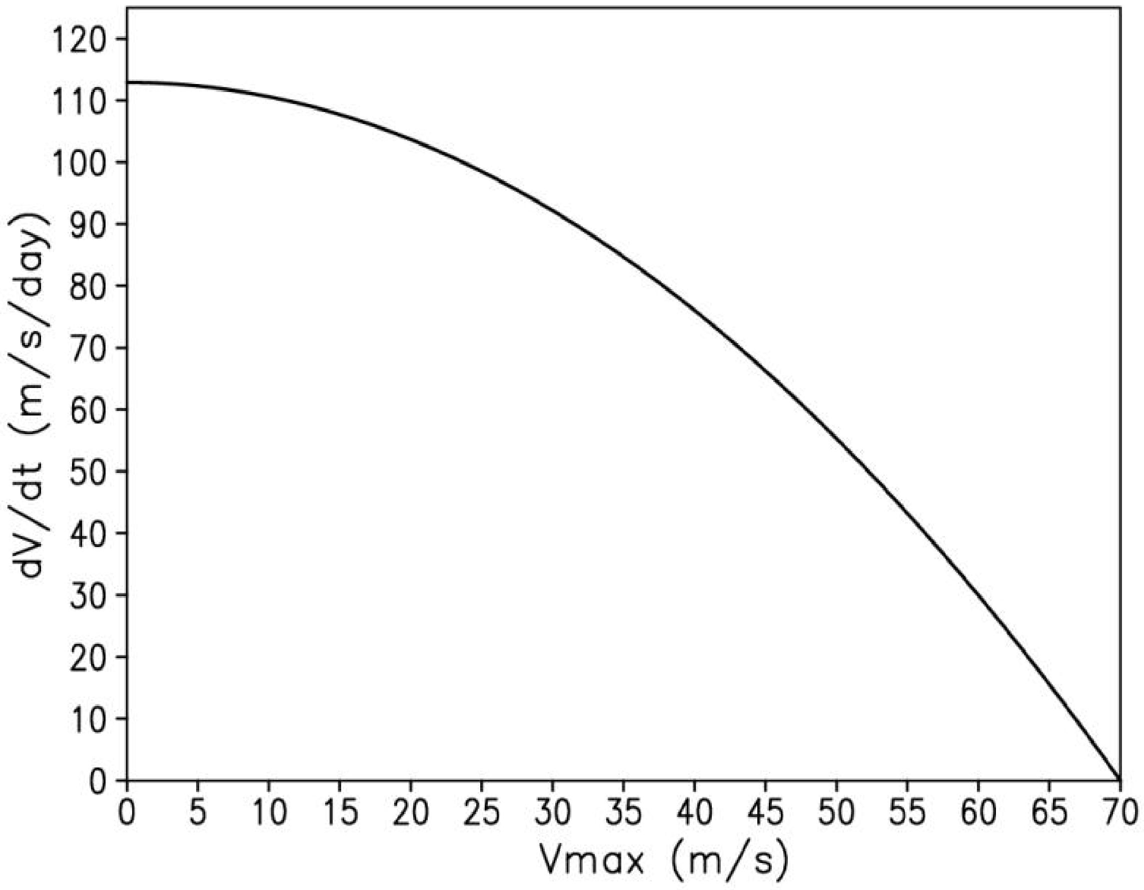
Emanuel (2012)



Some weaknesses of the early time-dependent theories

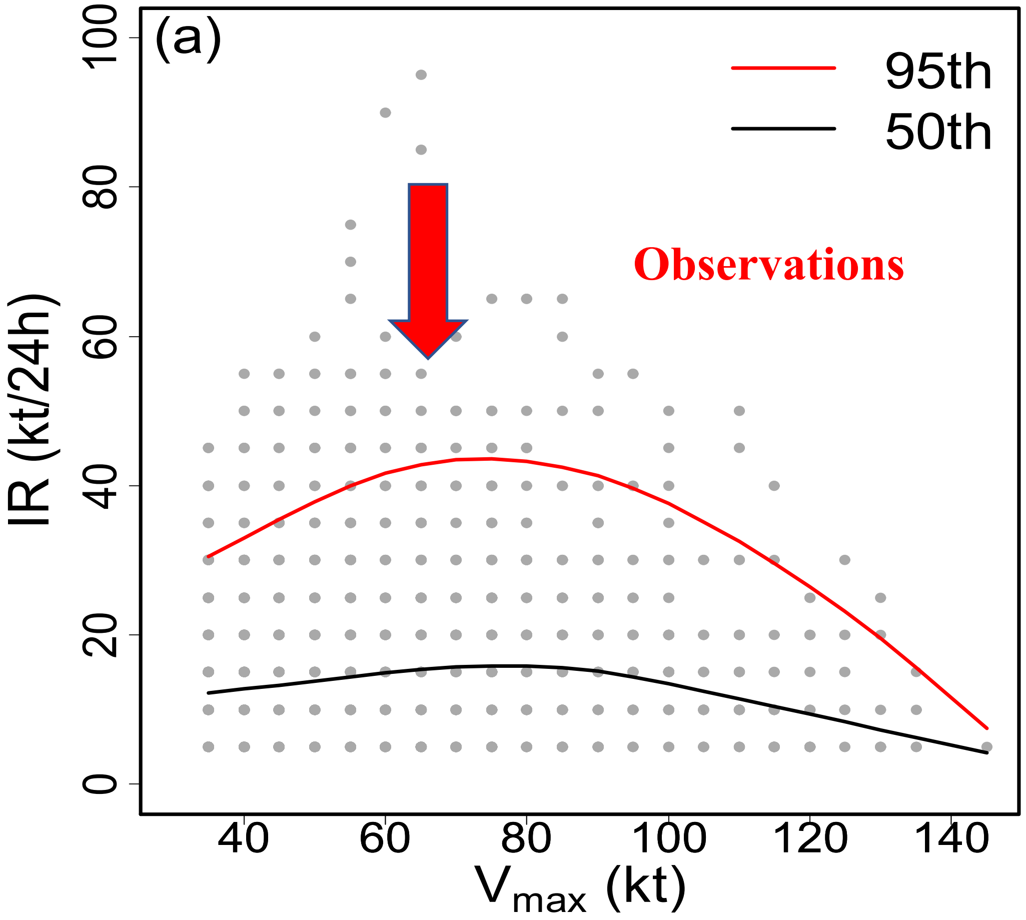
$$\frac{\partial V_{max}}{\partial \tau} = \frac{C_D}{H}(\mu V_{mpi}^2 - V_{max}^2)$$

Ozawa & Shimokawa (2015)



The steady-state intensity is only 70% of the corresponding V_{mpi}!

Xu and Wang (2015)



Some weaknesses of the early time-dependent theories

Basic understanding on the deficiencies of the current theories

For an axisymmetric TC vortex, we have the budget equation

$$\frac{\partial V_{max}}{\partial t} = -u_{rm}\xi_{a,rm} - w_{rm}\frac{\partial V_{max}}{\partial z} + F_{vrm}$$

Intensification potential

$$\frac{\partial V_{max}}{\partial t} \propto -u_{rm}\xi_{a,rm} - w_{rm}\frac{\partial V_{max}}{\partial z}$$

Frictional weakening potential

$$\frac{\partial V_{max}}{\partial t} \propto -\frac{C_D}{h}V_{max}^2$$

$$\frac{\partial V_{max}}{\partial \tau} = \frac{C_k}{2h}\left(V_{mpi}^2 - V_{max}^2\right)$$

Emanuel (2012)

$$\frac{\partial V_{max}}{\partial \tau} = -\frac{C_k}{2h}V_{max}^2$$

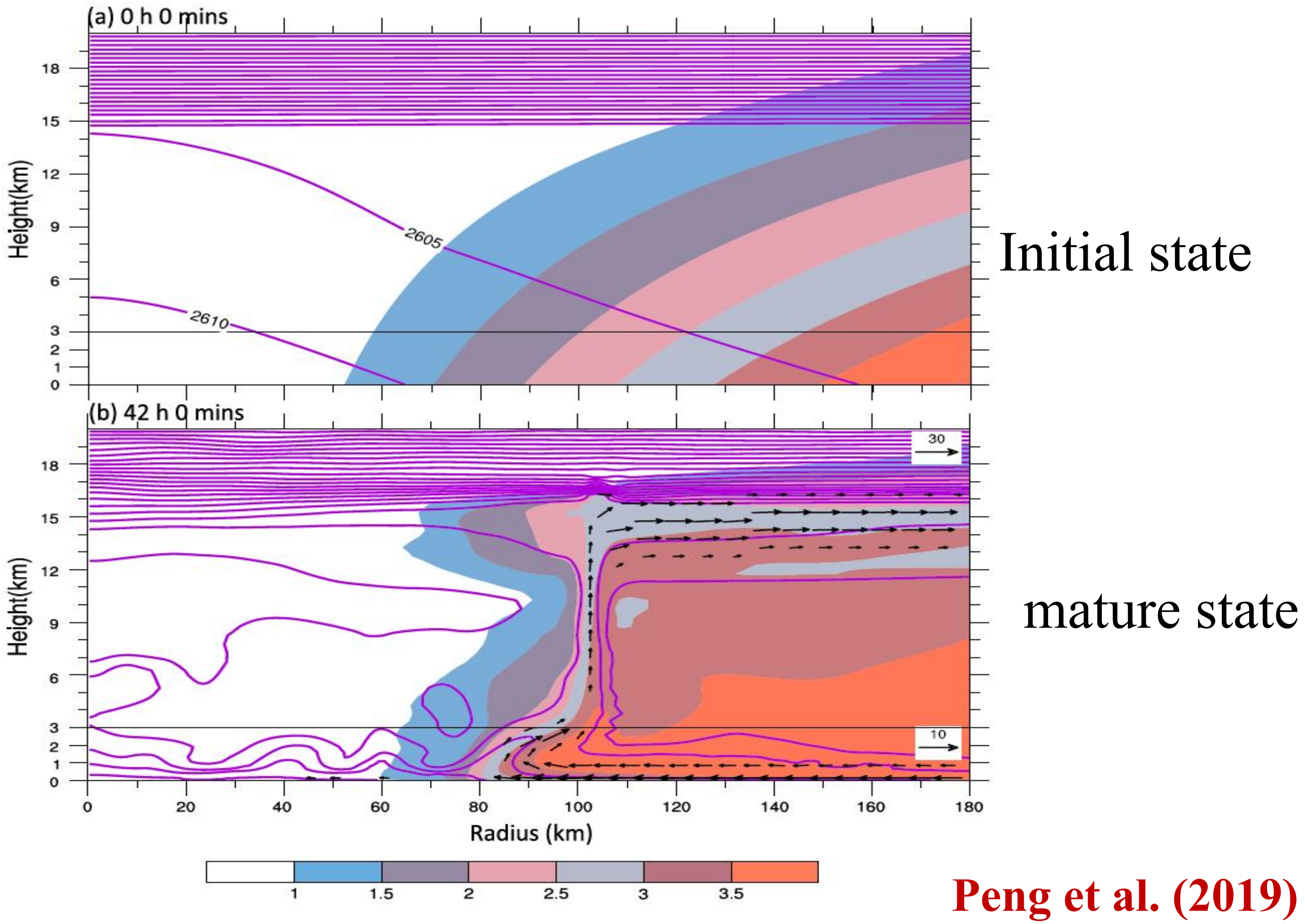
?

Some weaknesses of the early time-dependent theories

Possible reasons for the discrepancies

1. The material surface of the RMW, and thus conservation of ($V_{max} \times R_m$)

2. The moist-neutral eyewall ascent is not satisfied in an intensifying storm



Peng et al. (2019)

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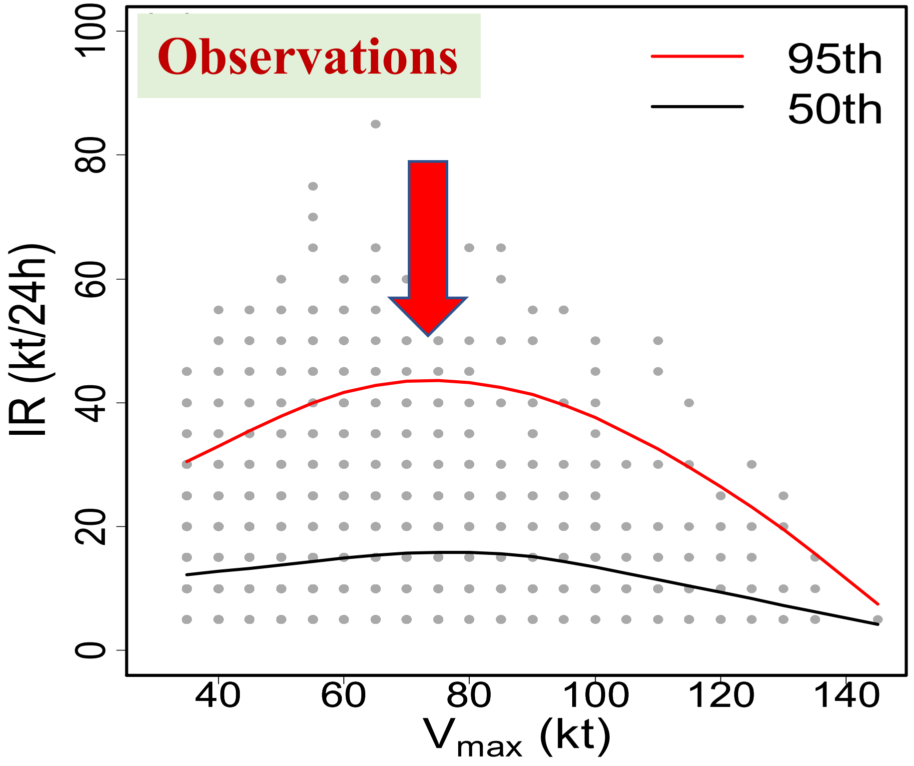
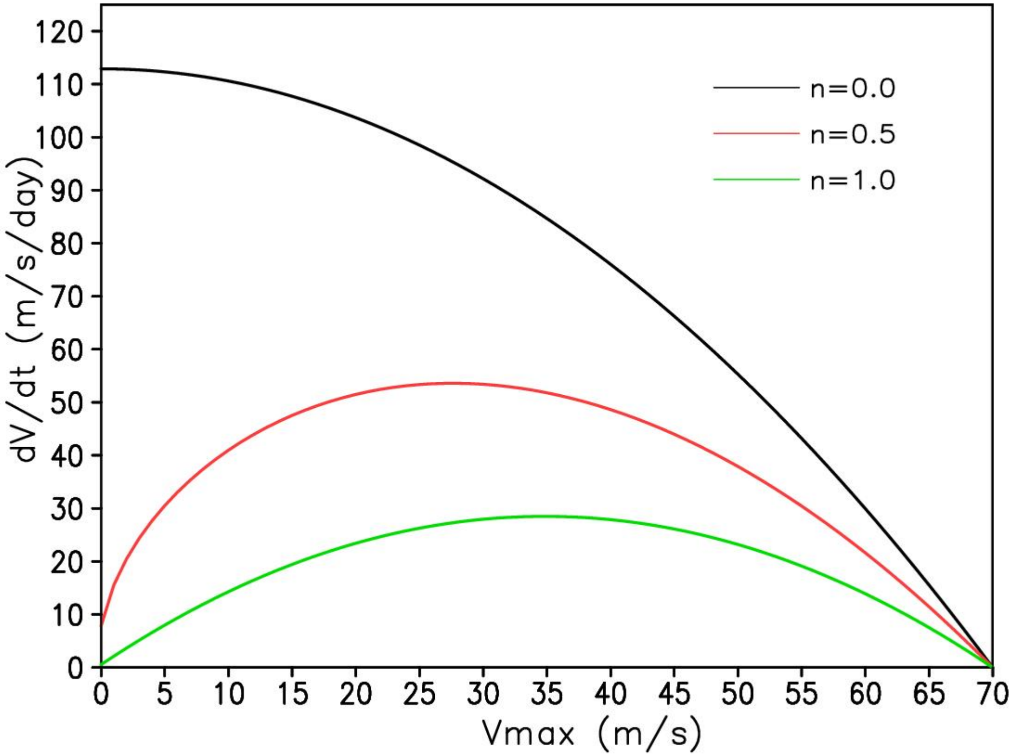
A modified energetically based time-dependent theory





$$\frac{\partial V_{max}}{\partial \tau} = \frac{C_D}{H}(\mu V_{mpi}^2 - V_{max}^2)$$

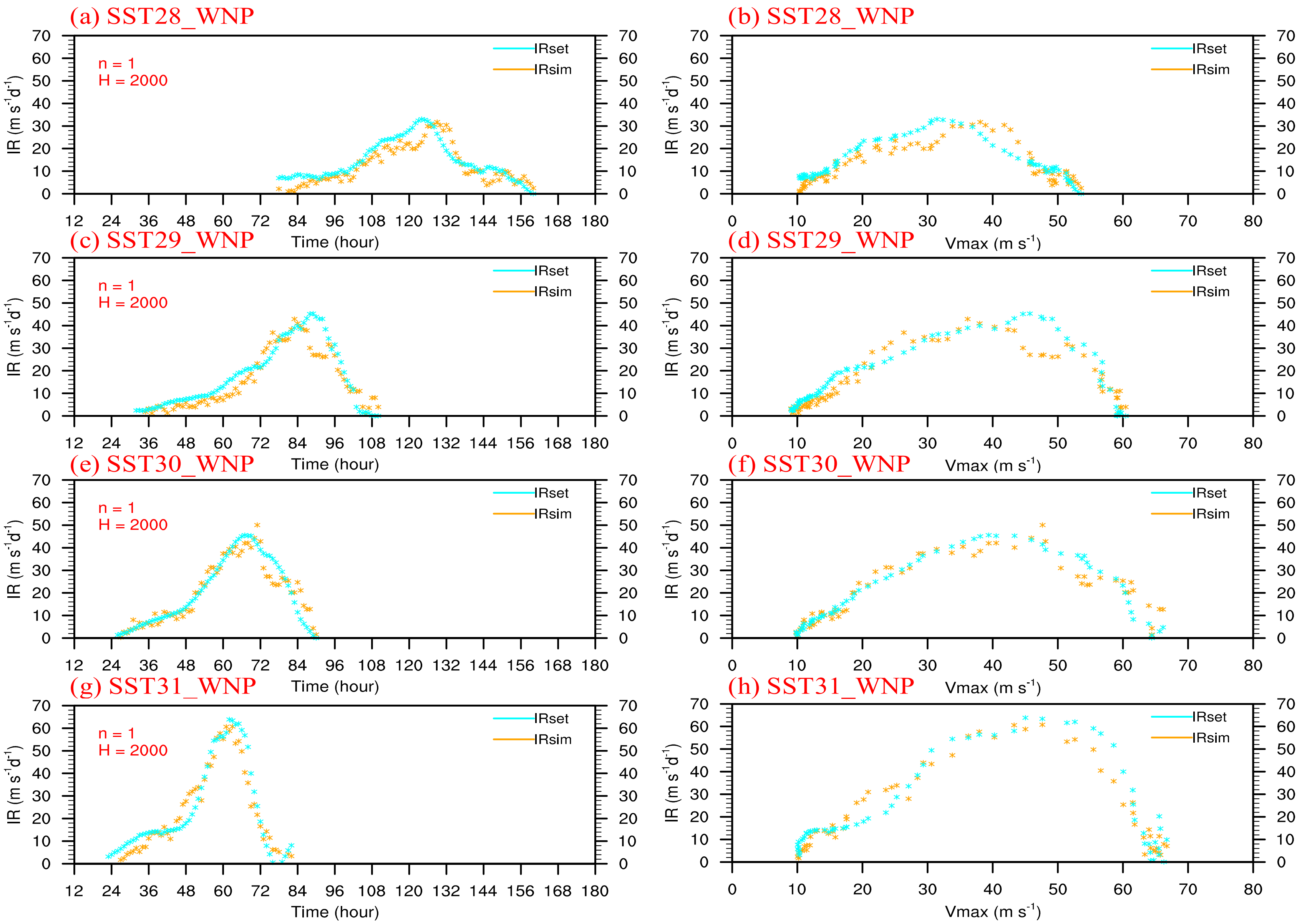
$$\frac{\partial V_{max}}{\partial \tau} = \frac{C_D}{H}(E V_{mpi}^2 - V_{max}^2)$$

$$\mathrm{E} = \left(\frac{I}{I_{mpi}}\right)^n = \left[\frac{\sqrt{\left(f+\frac{2V}{r}\right)\left(f+\frac{\partial rV}{r\partial r}\right)}\Big|_{rm}}{\sqrt{\left(f+\frac{2V}{r}\right)\left(f+\frac{\partial rV}{r\partial r}\right)}\Big|_{rmpi}}\right]^n$$

Wang et al. (2021a)

A modified energetically based time-dependent theory

Time dependence



Intensity dependence

Wang et al. (2021a)

A new dynamically based time-denpendent theory

We start with the following slab boundary layer equations in Cartisian coordinates

$$\frac{\partial V_b}{\partial t} + u_b \frac{\partial M_b}{r \partial r} = -\frac{C_D}{h} \left|\overrightarrow{\boldsymbol{V}_{10}}\right| V_{10},$$

$$\frac{\partial s_b}{\partial t} + u_b \frac{\partial s_b}{\partial r} = \frac{C_k}{h} \beta \left|\overrightarrow{\boldsymbol{V}_{10}}\right| (s_0^* - s_b),$$

β ($\leq$1.0) is an efficiency parameter describing effects of sub-saturation or downdraft.

Assuming that the boundary layer is in thermodynamic quasi-equilibrium

$$u_b \frac{\partial s_b}{\partial r} = \frac{C_k}{h} \beta \left|\overrightarrow{\boldsymbol{V}_{10}}\right| (s_0^* - s_b)$$

A key assumption well supported by full-physics model simulations

$$h \frac{\partial V_b}{\partial \tau} = -\frac{1}{r_m} \frac{\partial M_b}{\partial r} C_k \beta \left|\overrightarrow{\boldsymbol{V}_{\mathbf{10}}}\right| (s_0^* - s_b) / \frac{\partial s_b}{\partial r} - C_D \left|\overrightarrow{\boldsymbol{V}_{\mathbf{10}}}\right| V_{10}$$

Combining the two equations, we have

$$\frac{\partial V_{max}}{\partial \tau} = \frac{\alpha}{h} \left[-\frac{1}{r_m} \frac{\partial M}{\partial s}\bigg|_{b,r_m} C_k \beta V_{max} (s_0^* - s_b)|_{r_m} - C_D V_{max}^2 \right]$$

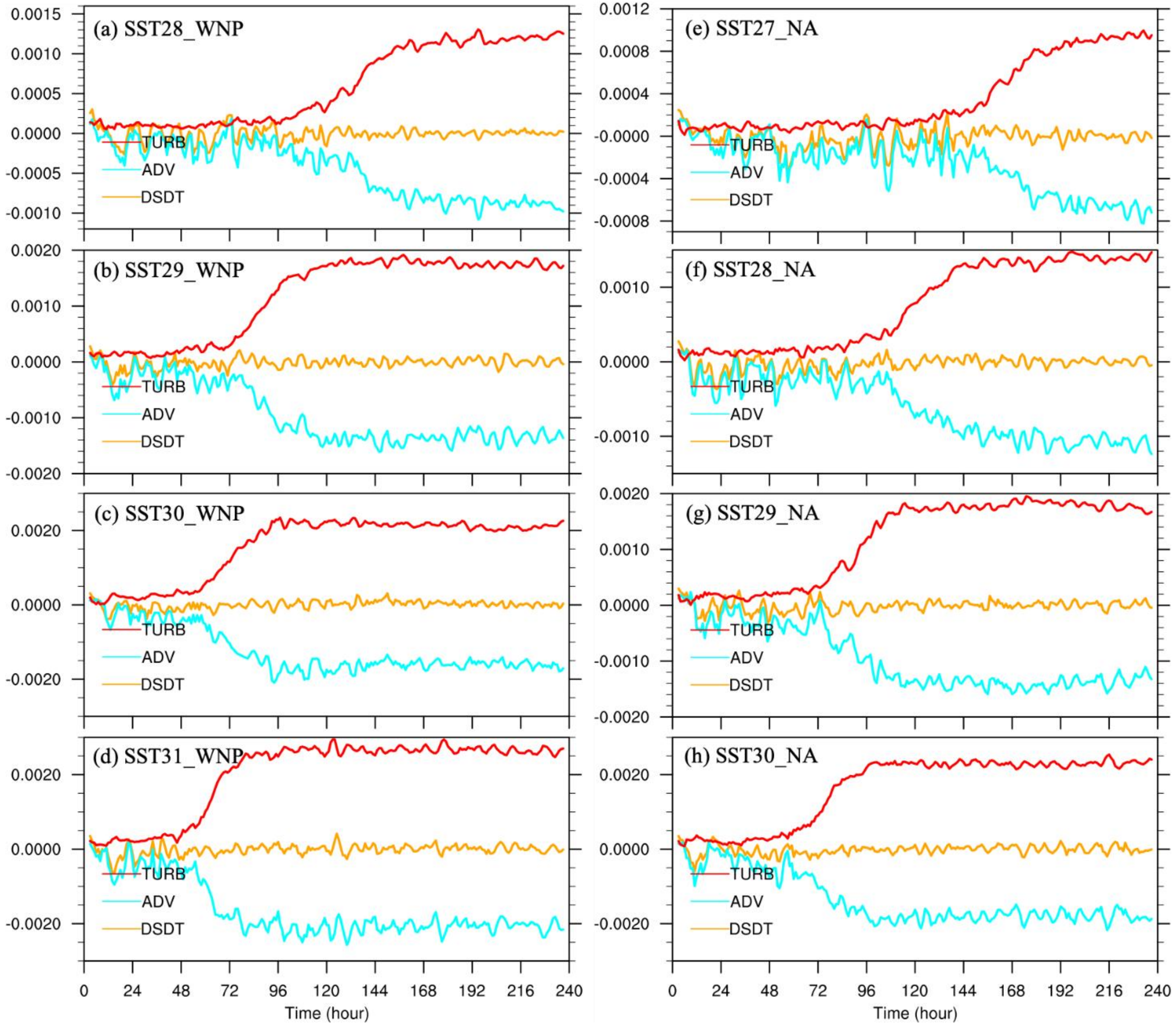
$$\frac{\partial M}{\partial s}\bigg|_{b,r_m} \cong \frac{\partial M}{\partial s}\bigg|_{h,r_m}$$

Wang et al. (2021b)

Moist entropy budget equation

$$\frac{\partial \theta_e}{\partial t} = -u\frac{\partial \theta_e}{\partial r} - w\frac{\partial \theta_e}{\partial z} + F_{\theta_e} + D_{\theta_e}$$

The thermodynamic quasi-equilibrium assumption is well supported by full-physics model CM1 simulations



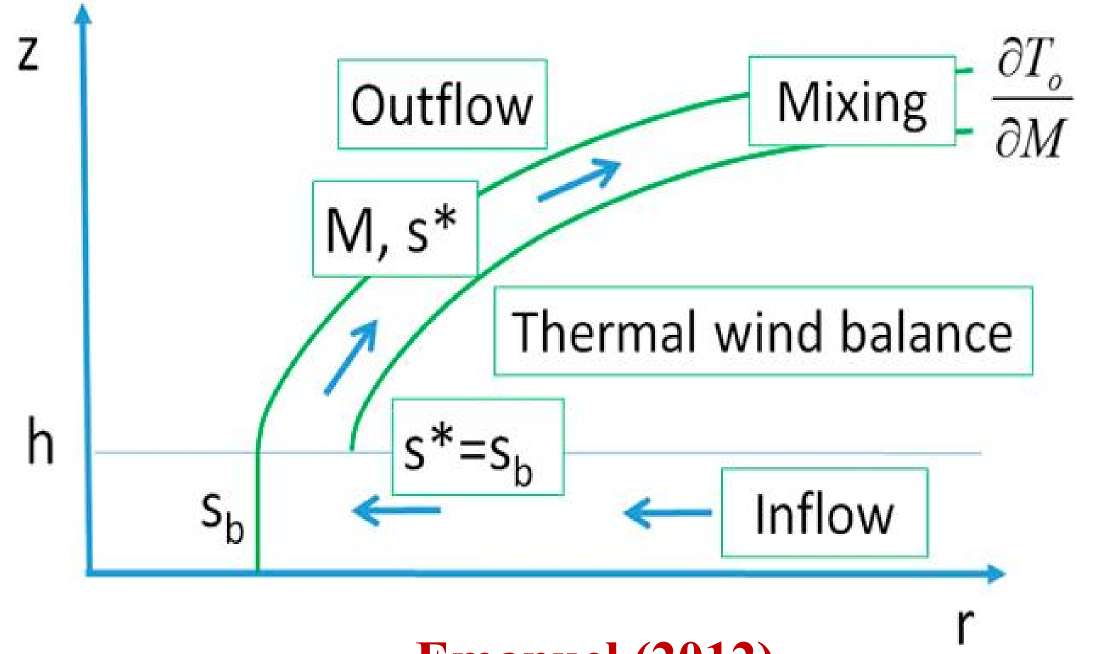
A new dynamically based time-denpendent theory

Following Emanuel (986, 2012), for a mature storm, integrating the thermal wind relationship below

$$\frac{1}{r^3}\left(\frac{\partial r}{\partial p}\right)_M = \frac{1}{2M}\frac{\partial s}{\partial M}\left(\frac{\partial T}{\partial p}\right)_s$$

along the moist neutral eyewall ascent

$$\left.\frac{dM}{ds}\right|_{h,r_m} = -\frac{T_b - T_0}{M_{h,r_m}\left(\frac{1}{r_m^2} - \frac{1}{r_0^2}\right)}$$



Emanuel (2012)

Introducing a new *ad-hoc* parameter *A'* to measure the degree of the congruence between the *M* and *S** surface

$$\boxed{\left.\frac{\partial M}{\partial s}\right|_{b,r_m} \cong \left.\frac{\partial M}{\partial s}\right|_{h,r_m} = -A'\frac{T_b - T_0}{M_{h,r_m}\left(\frac{1}{r_m^2} - \frac{1}{r_0^2}\right)}}$$

$$\mathbf{0 \le A' \le 1.0}$$

Wang et al. (2021b)

A new dynamically based time-dependent theory

The tangential wind budget equation following the RMW

$$\frac{\partial V_{max}}{\partial \tau} = \frac{\alpha}{h}\left[\frac{r_m}{M_{h,r_m}}\varepsilon A'\beta C_k V_{max}(k_0^* - k_b)|_{r_m} - C_D V_{max}^2\right]$$

Using the definition of E-MPI, the above equation can be rewritten as

$$\frac{\partial V_{max}}{\partial \tau} = \frac{\alpha C_D}{h}(AV_{mpi}^2 - V_{max}^2)$$

The New IR equation

where $A = \beta A'$, and $V_{mpi}^2 = \frac{C_k}{C_D}\varepsilon(k_0^* - k_b)$

A natural option is to assume A to be a function of the relative intensity, namely $A = (\frac{V_{max}}{V_{mpi}})^n$ with n (> 0) is a power constant calibrated using idealized simulations and best-track data, which gives $n = 3/2$.

$$\frac{\partial V_{max}}{\partial \tau} = \frac{\alpha C_D}{h}V_{mpi}^2\left[\left(\frac{V_{max}}{V_{mpi}}\right)^{3/2} - \left(\frac{V_{max}}{V_{mpi}}\right)^2\right]$$

Wang et al. (2021b)

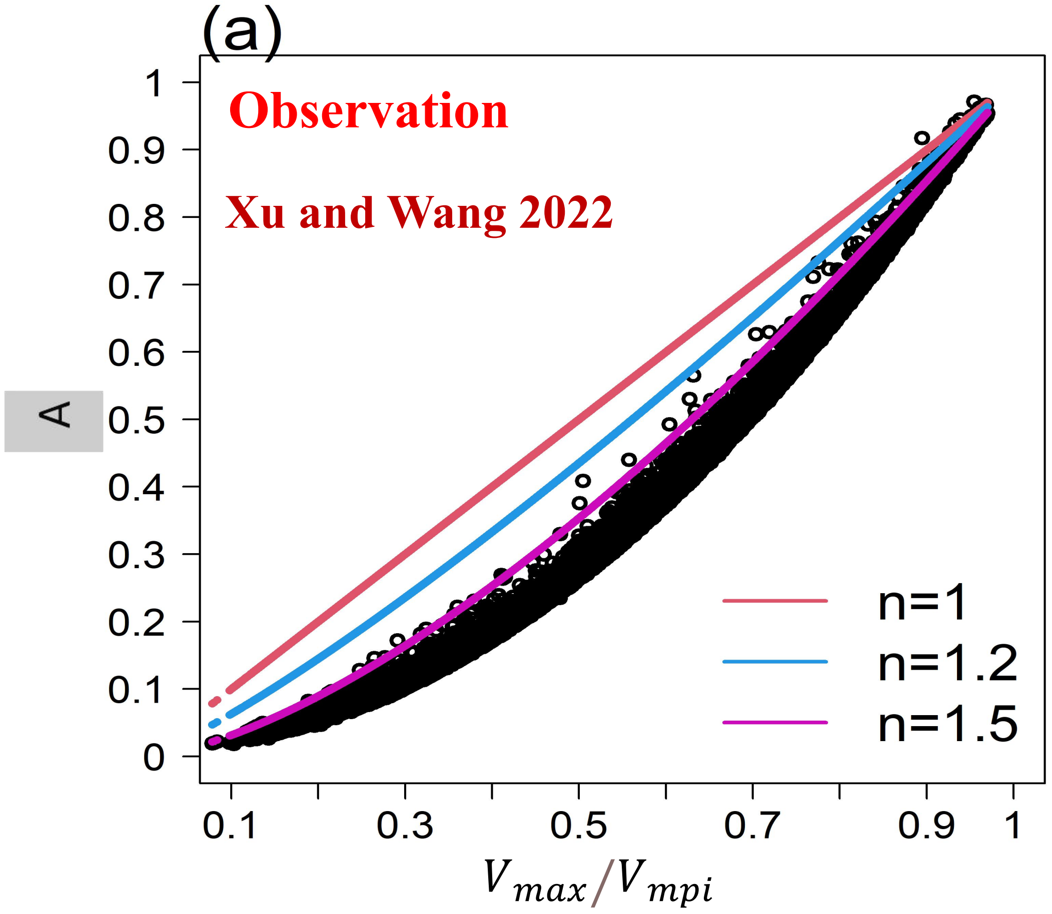
A new dynamically based time-dependent theory

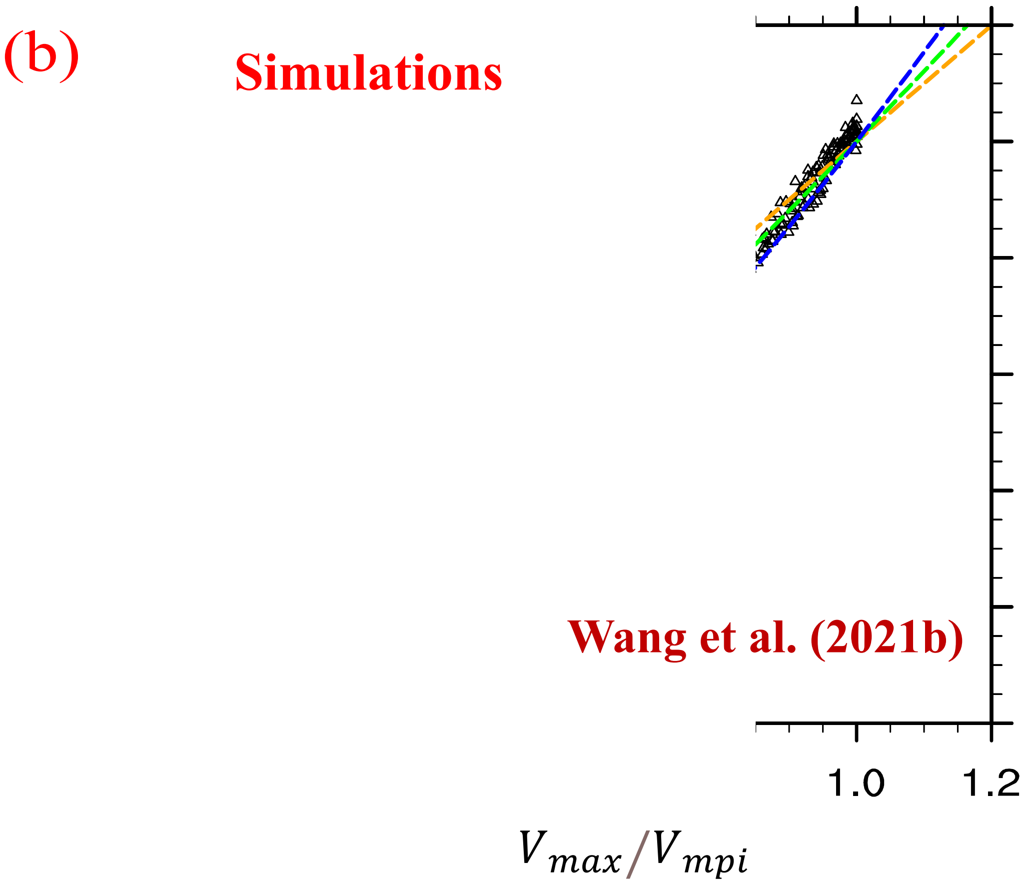
$$\frac{\partial V_{max}}{\partial \tau} = \frac{\alpha C_D}{h}(AV_{mpi}^2 - V_{max}^2)$$

$$A = (\frac{V_{max}}{V_{mpi}})^n$$

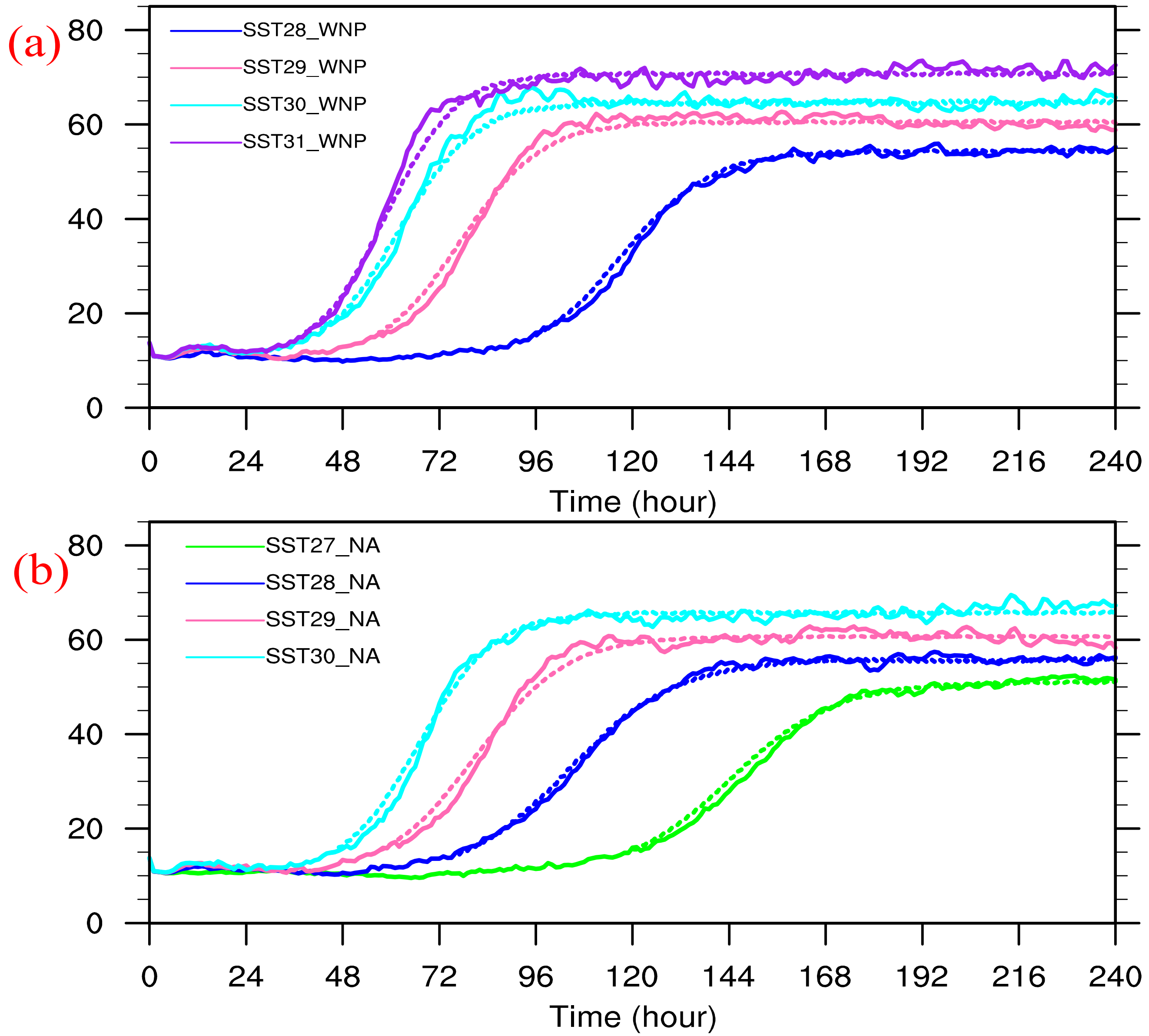
n=3/2 gives the best fiting for both

A is supported by the fitting based on the best-track data and full physics model simulations





A new dynamically based time-dependent theory



Idealized simulations using the full physics CM1 model

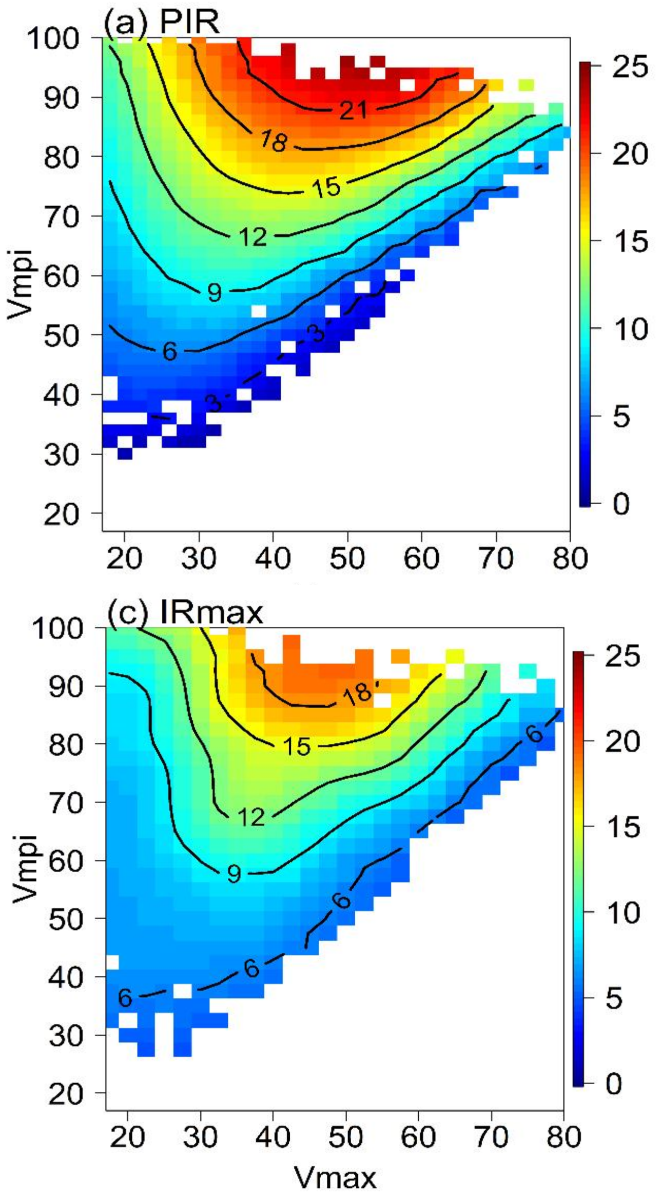
$$\frac{\partial V_{max}}{\partial \tau} = \frac{\alpha C_D}{h} V_{mpi}^2 \left[\left(\frac{V_{max}}{V_{mpi}} \right)^{3/2} - \left(\frac{V_{max}}{V_{mpi}} \right)^2 \right]$$

Wang et al. (2021b)

A new dynamically based time-dependent theory

Verification using best-track data

PIR – Potential intensification rate



Theoretical estimate

Top 99% averaged IR from the best-track data

Xu and Wang (2022)

Equivalence of the energetically based & dynamically based time-dependent theories

Energetically based $$\frac{\partial V_{max}}{\partial \tau} = \frac{C_D}{H}\left(EV_{mpi}^2 - V_{max}^2\right)$$

Dynamically based $$\frac{\partial V_{max}}{\partial \tau} = \frac{\alpha C_D}{h}\left(AV_{mpi}^2 - V_{max}^2\right)$$

$$\int\int \rho \frac{\partial}{\partial t}\left(\frac{1}{2}\left|\vec{V}\right|^2\right) rdrdz = E\int \rho \epsilon C_k \left|\vec{V}\right| (\kappa_o^* - \kappa_a) rdr - \int \rho C_D \left|\vec{V}\right|^3 rdr$$

Ozawa & Shimokawa (2015) approximated

$$\int\int \rho \frac{\partial}{\partial t}\left(\frac{1}{2}V^2\right) rdrdz = H\bar{\rho}V_{max}\frac{\partial V_{max}}{\partial \tau}$$

Here, we assume the volume-averaged wind speed

$$\int\int \rho \frac{\partial}{\partial t}\left(\frac{1}{2}V^2\right) rdrdz = H\bar{\rho}\bar{V}\frac{\partial \bar{V}}{\partial \tau}$$

$$H\bar{\rho}\bar{V}\frac{\partial \bar{V}}{\partial \tau} = E\rho_0 \varepsilon C_k V_{max}(\kappa_o^* - \kappa_a)_{rm} - \rho_0 C_D V_{max}^3$$

$\mu = \bar{V}/V_{max}$ $\quad$ $\alpha/h = \rho_0/(\bar{\rho}H\mu^2)$ $\longrightarrow$ $$\frac{\partial V_{max}}{\partial t} = \frac{\alpha C_D}{h}\left(EV_{mpi}^2 - V_{max}^2\right)$$

Some refinements to the time-dependent theory

Inclusion of dissipative heating

$$\frac{\partial V_{max}}{\partial \tau} = \frac{\alpha}{h}\left[\frac{r_m}{M_{h,r_m}} \varepsilon A' \beta C_k V_{max}(k_0^* - k_b)|_{r_m} - C_D V_{max}^2\right]$$

$$\frac{\partial V_{max}}{\partial \tau} = \frac{\alpha}{h}\left[\frac{r_m}{M_{h,r_m}} \varepsilon A' \beta \left\langle C_k V_{max}\left(k_0^* - k_b - \frac{1}{2}\delta\gamma V_{max}^2\right)\Big|_{r_m} + \gamma C_D V_{max}^3\right\rangle - C_D V_{max}^2\right]$$

The equation of intensification rate becomes

$$\frac{\partial V_{max}}{\partial \tau} = \frac{\alpha C_D}{h}\left\{A V_{EMPI}^2 - V_{max}^2 + \gamma A \epsilon \left(1 - \frac{\delta C_k}{2\gamma C_D}\right) V_{max}^2\right\}$$ With dissipative heating (DH)

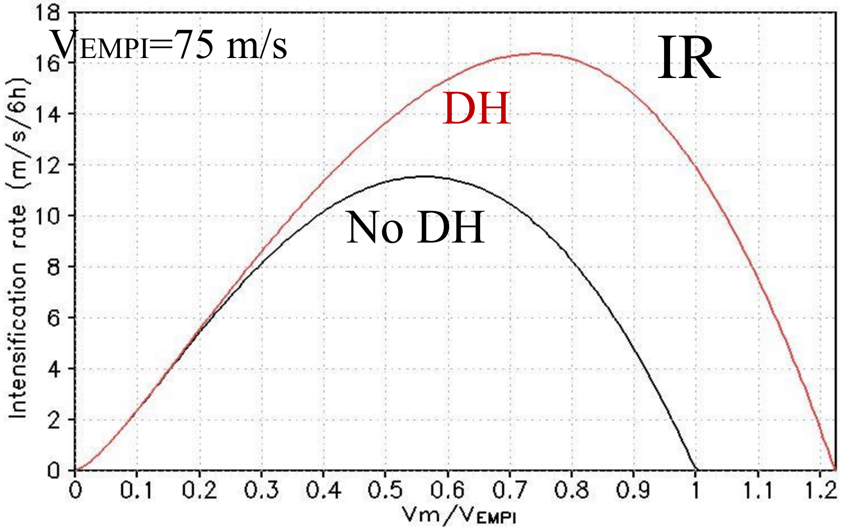
$$V_{mpi} = \frac{V_{EMPI}}{\sqrt{1 - \gamma\varepsilon\left(1 - \frac{\delta C_k}{2C_D}\right)}}$$

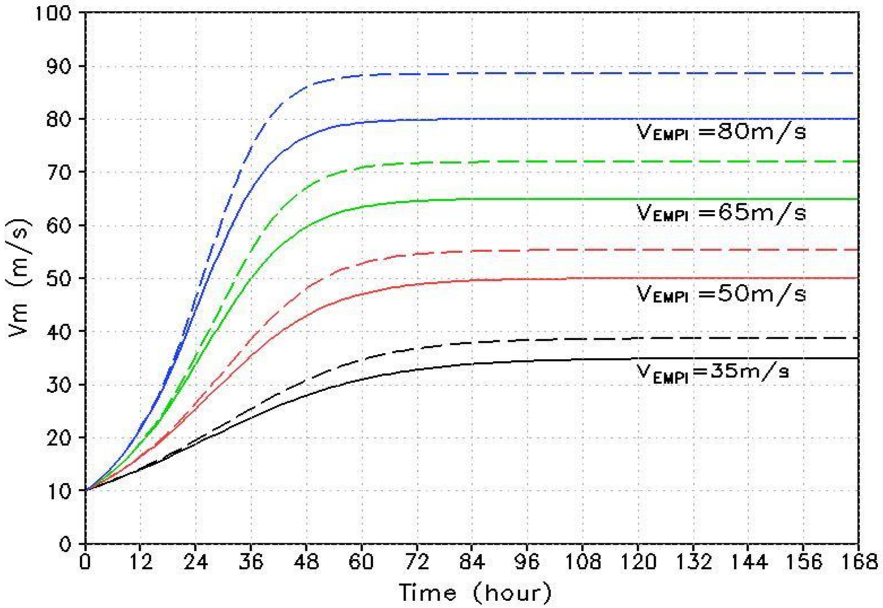
Without dissipative heating

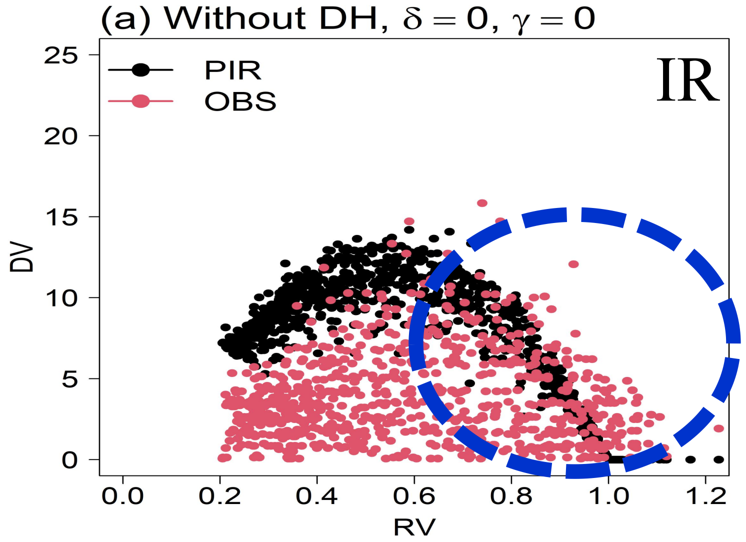
$$\frac{\partial V_{max}}{\partial t} = \frac{\alpha C_D}{h}(A V_{EMPI}^2 - V_{max}^2)$$

Wang et al. (2022)

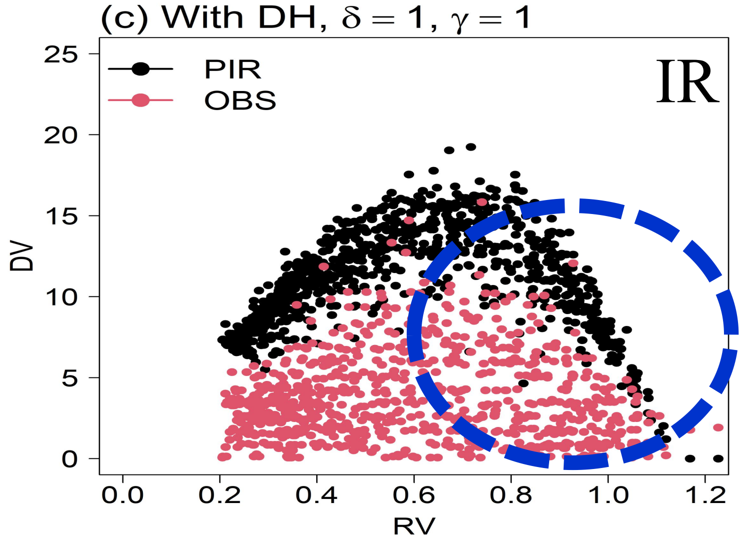
Contribution of dissipative heating to TC IR







Without DH considered underestimates IRs of strong TCs



With DH considered reduces underestimates of IRs of strong TCs

Wang et al. (2022)

Inclusion of isothermal expansion effect and SST-Ta

$$\frac{\partial V_{max}}{\partial \tau} = \frac{\alpha C_D}{h}\left\{AV_{EMPI}^2 - V_{max}^2 + \gamma A \epsilon\left(1 - \frac{\delta C_k}{2\gamma C_D}\right) V_{max}^2\right\}$$

$$V_{EMPI}^2 = \frac{C_k}{C_D}\varepsilon(k_0^* - k_b)|_{r_m}$$

$$= \frac{C_k}{C_D}\varepsilon[c_p(T_s - T_a) + L_v(q^*_{vs}|_{r_m} - q_{va0})]$$

$$q_{vs}^* = 0.622\frac{e_{so}}{p_m - e_{so}} = q_{vs0}^*\left(\frac{p_e - e_{so}}{p_m - e_{so}}\right)$$

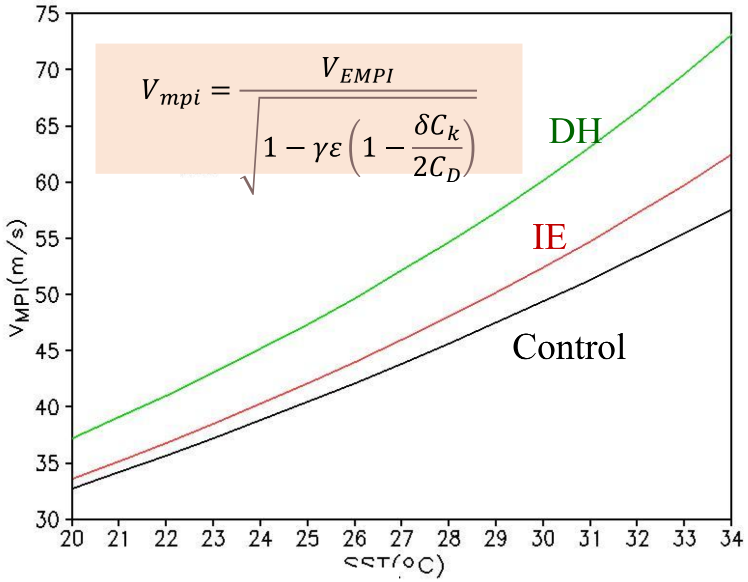
$$q_{va0} = RH \times q_{va0}^* = RH \times q_{vs0}^*\left[1 - \frac{0.622 L_v}{R_d T_s^2}(T_s - T_a)\right]$$

$$\frac{\partial V_{max}}{\partial \tau} = \frac{\alpha C_D}{h}\left\{AV_{MPI0}^2 - \left[1 - A\kappa - \gamma A \varepsilon\left(1 - \frac{\delta C_k}{2C_D}\right)\right] V_{max}^2\right\} \qquad \kappa = \frac{C_k}{C_D}\varepsilon\frac{cL_v q_{vs0}^*}{2R_d T_s}$$

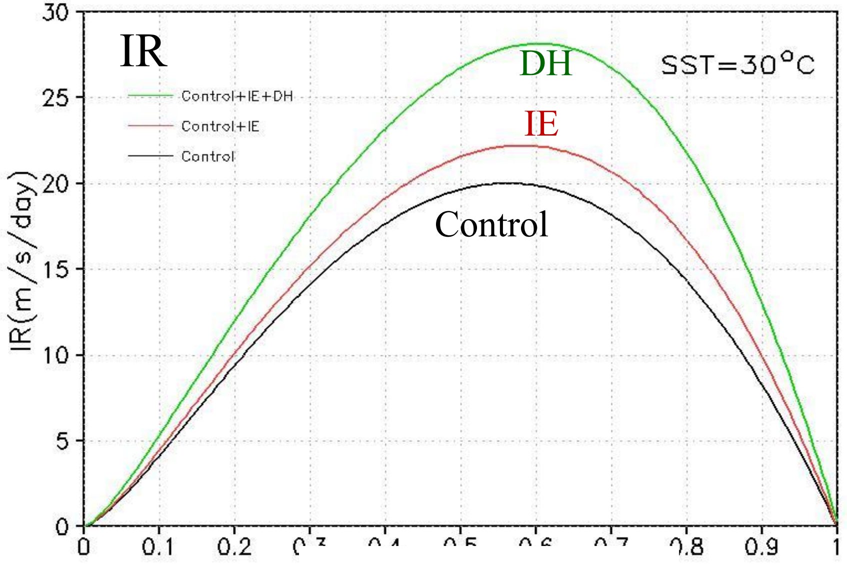
$$V_{MPI0}^2 = \frac{C_k}{C_D}\varepsilon[c_p(1+\mu)(T_s - T_a) + (1 - RH)\, L_v q_{vs0}^*] \qquad \mu = \frac{0.622 RH L_v^2 q_{vs0}^*}{c_p R_d T_s^2}$$

Wang et al. (2023)

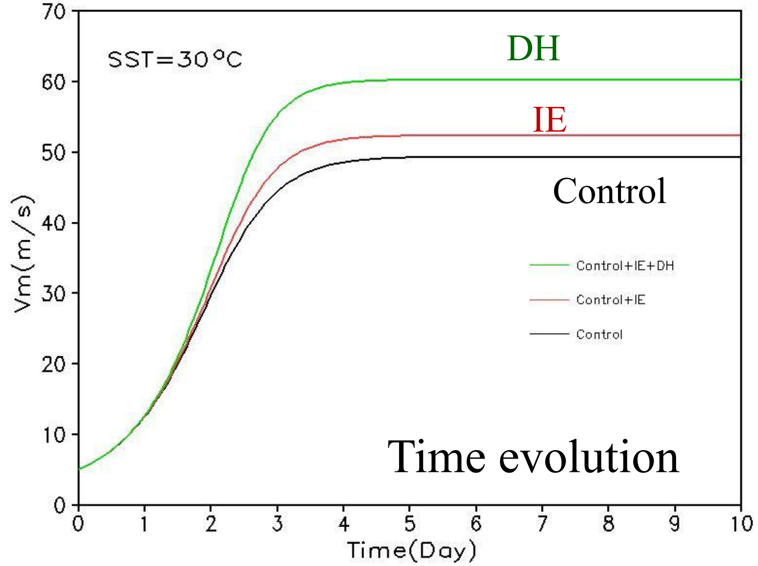
Effect of isothermal expansion

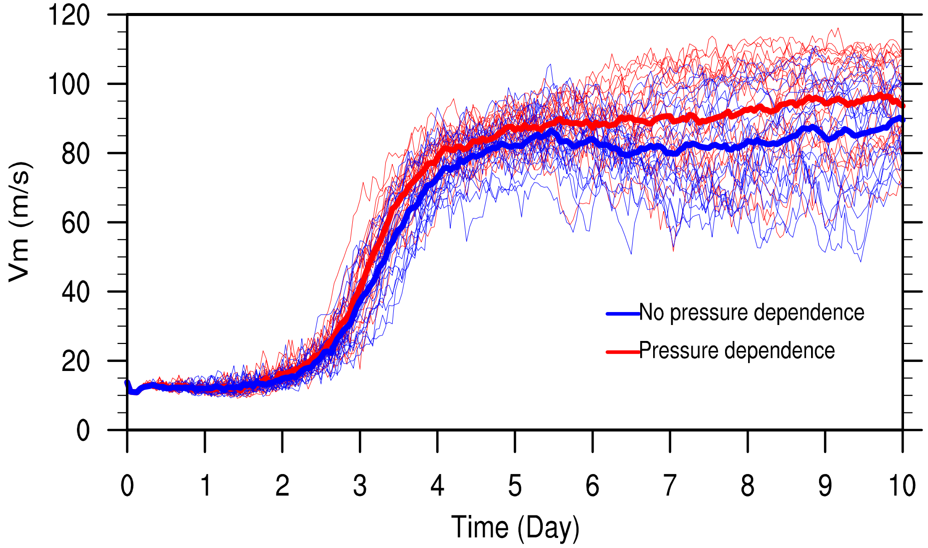


SST



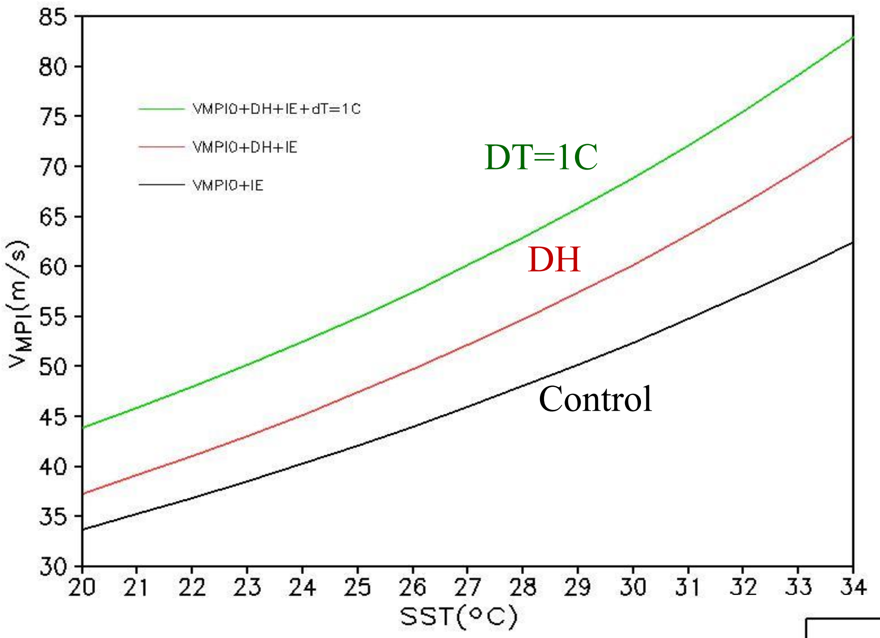
Relative intensity

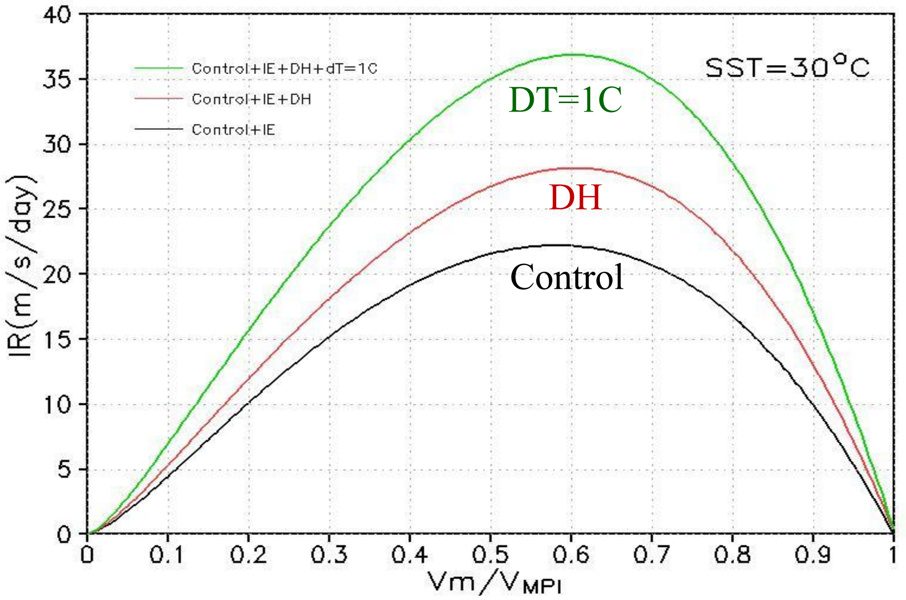


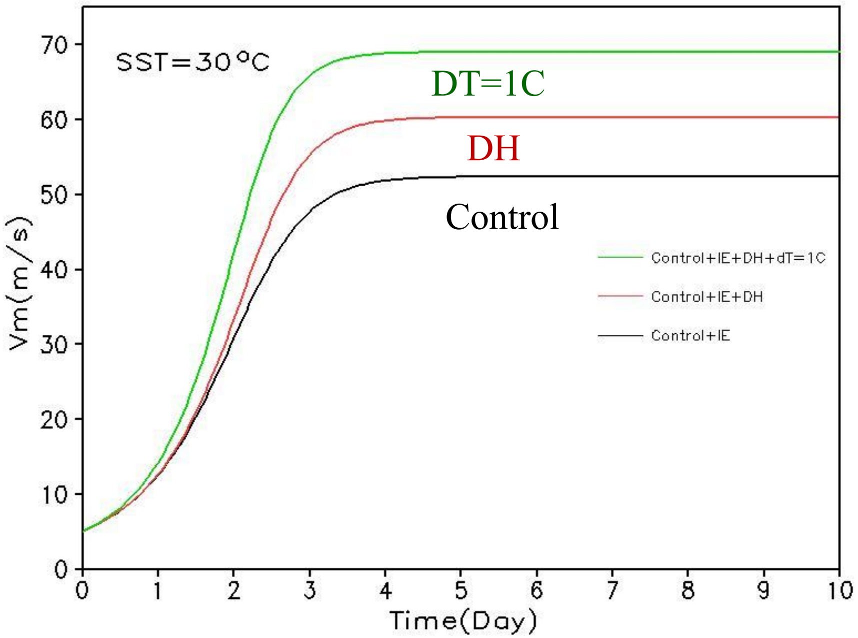


Wang et al. (2023)

Effect of air-sea temperature difference







Wang et al. (2023)

A brief summary of the new theoretical developments

- A unified time-dependent theory of TC intensification has been constructed, which overcomes several weaknesses in previous energetically based and dynamically based time-dependent theories.
- Several new refinements have been achieved. They are the inclusions of dissipative heating, isothermal expansion, and explicit air-sea temperature difference.
- Isothermal expansion can lead to an increase in IR by 20% and in MPI by 10%; DH can lead to an increase in IR by 45% and in MPI by 22% at the tropical conditions, especially for very strong TCs.
- A new result is the significant increase in both the IR and MPI with the increasing air-sea temperature difference, which is almost independent of SST.
- The MPIR is proportional to the square of MPI. As a result, under global warming, TCs will be not only more intense but also intensify more rapidly.

Outline

- Classic views on tropical cyclone (TC) intensification
- Early efforts toward time-dependent theories
- A unified time-dependent theory of TC intensification
- **Applications:**

  Quantifying environmental effects on TC intensity change

  Prediction of TC intensity
- Future directions

Applications (1)
Quantifying environmental effects on TC intensity change

We can introduce an *ad-hoc* environmental ventilation ***B*** **($0 \leq B \leq 1$),** which reflects all environmental processes that are detrimental to the moist-neutral condition of the eyewall updraft (such as the ventilations due to vertical wind shear, fast translation of the TC, and dry air intrusion due to interaction with mid-latitude westerly trough).

$$\frac{\partial V_{max}}{\partial \tau} = \frac{\alpha C_D}{h} V_{mpi}^2 \left[\boldsymbol{B} \left(\frac{V_{max}}{V_{mpi}} \right)^{3/2} - \left(\frac{V_{max}}{V_{mpi}} \right)^2 \right]$$

$$B = B(VWS,\ V_{trans},\ RH_m, \cdots)$$

B will be determined based on deep machine learning using the best-track TC data and reanalysis data, and then numerically integrating the IR equation to predict TC intensity.

Xu, Wang, & Yang (2023)

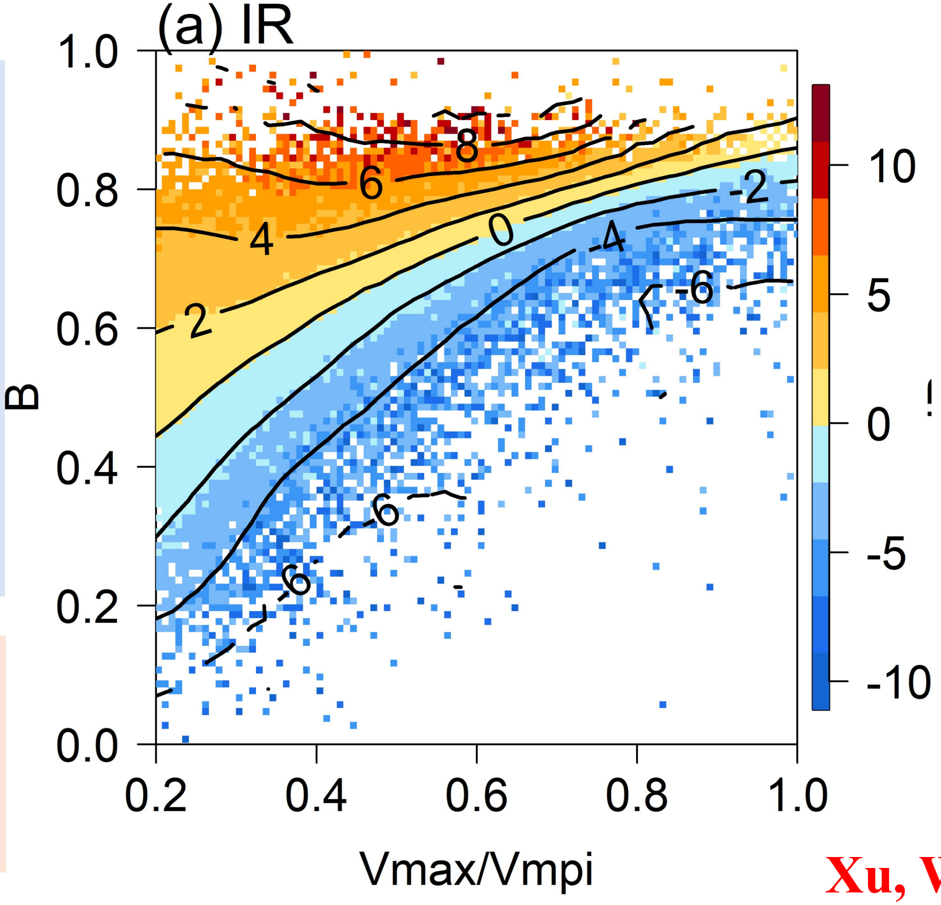
Applications (1)
Quantifying environmental effects on TC intensity change

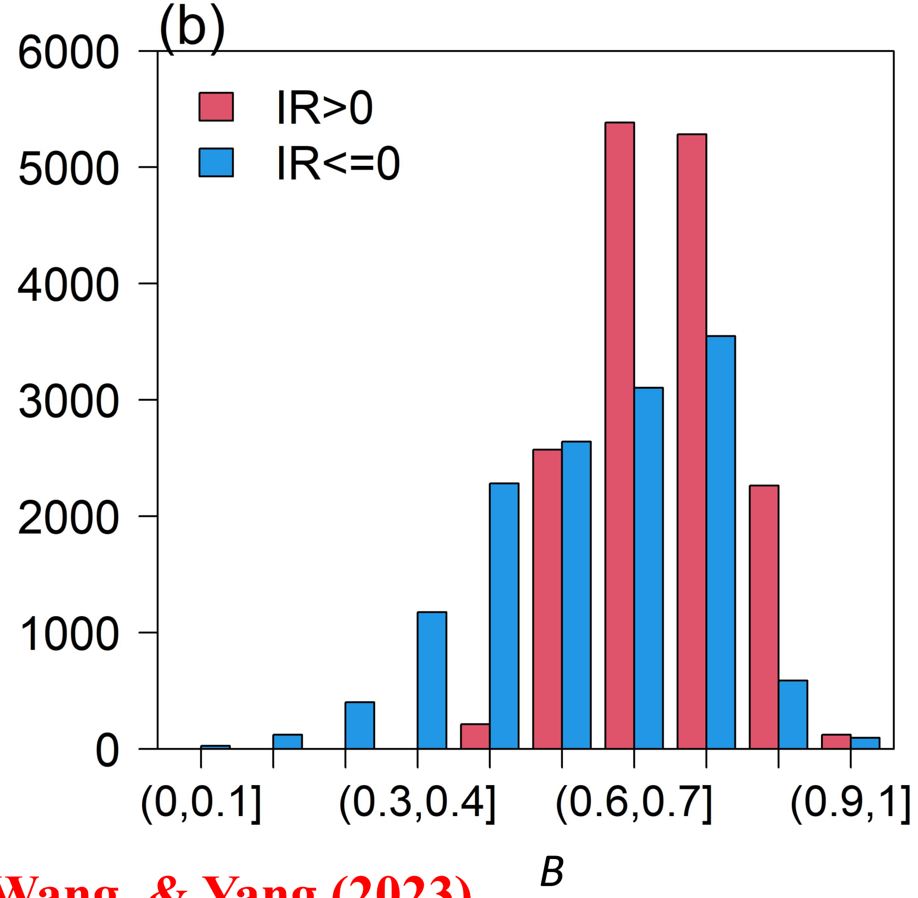
$$\frac{\partial V_{max}}{\partial \tau} = \frac{\alpha C_D}{h} V_{mpi}^2 \left[\boldsymbol{B} \left(\frac{V_{max}}{V_{mpi}} \right)^{3/2} - \left(\frac{V_{max}}{V_{mpi}} \right)^2 \right]$$

We used α=0.75, C_D=2.4·10^{-3}, h=2000 m

The best-track data of TCs over the North Atlantic, the central and eastern North Pacific during **1982–2021** and over the western North Pacific during **1990–2020**.

$IR = \frac{\partial V_{max}}{\partial \tau} \geq 0$, when $B \geq \left(\frac{V_{max}}{V_{mpi}} \right)^{\frac{1}{2}}$.





Xu, Wang, & Yang (2023)

Applications (1)
Quantifying environmental effects on TC intensity change

B is contributed by various individual environmental ventilation parameters. $\boldsymbol{B} = B_1 \times B_2 \times B_3 \cdots B_6$. Here in total we chose 6 factors (Table below) obtained from the statistical hurricane intensity prediction scheme (SHIPS) database.

Variables	Unit	Description
Vm	m s^{-1}	Current TC intensity calculated by subtracting 40% of the translation speed from the best-track data
V_{mpi}	m s^{-1}	Maximum potential intensity (Emanuel 1986)
VWS	m s^{-1}	Deep-layer vertical wind shear defined as vector difference of winds averaged within 200-800 km between 850 and 200 hPa
COHC		Climatological ocean heat content (kJ cm^{-2}).
D200	$10^7 s^{-1}$	Divergence averaged within a radius of 1000 km from the TC center at 200 hPa
RHMD	%	Mean 500-700 hPa RH averaged between 200-800 km from the TC center
dMPI	m s^{-1}	MPI difference between t0 and t0+6h alone TC track
SPD	m s^{-1}	Translation speed of the TC system.

Applications (1)
Quantifying environmental effects on TC intensity change

$\boldsymbol{B} = B_1 \times B_2 \times B_3 \cdots B_6 = \prod_{j=1}^{6} B_j$, six factors are VWS, COHC, D200, RHMD, dPMI, SPD.

To quantify $\boldsymbol{B}$ and B_j, a two-stage machine learning (ML) approach was adopted:

1). eXtreme Gradient Boosting (XGBoost) (Chen and Guestrin 2016) was used to build a black-box but exact model of log(B) to capture the nonlinear relationship between $\log B$ and the selected 6 environmental factors. The XGBoost algorithm is a popular implementation of boosted regression trees (Friedman, 2001).

$$\log B = f(\text{VWS, COHC, D200, RHMD, dMPI, SPD})$$

2). SHapley Additive exPlanations (SHAP) technique (Lundberg et al. 2020) was used to transform the black-box model of log(B) to an additive model. SHAP is an additive feature attribution method that attributes values to each feature as the change in the expected model prediction when conditioning on that feature (Lundberg et al. 2020). For a specific input $\mathbf{x}$, the SHAP values ϕ_i for each feature i should sum up to the output $f(\mathbf{x})$:

$$f(\mathbf{x}) = \phi_0(f) + \sum_{i=1}^{M} \phi_i(f,\mathbf{x})$$

The sum of feature attributions -$\phi_i(f,\mathbf{x})$ matches the original model output $f(\mathbf{x})$, where $\phi_0(f) = E[f(\mathbf{X})]$ is the bias term.

Xu, Wang, & Yang (2023)

Applications (1)
Quantifying environmental effects on TC intensity change

$$\log B = f(\text{VWS, COHC, D200, RHMD, dMPI, SPD}) \qquad \log B_i = G + \sum_{j=1}^{6} S_{ij}$$

where G is the bias term (the overall mean of $\log B$); and S_{ij} ($j = 1,2, \ldots, 6$) are SHAP values corresponding to the 6 environmental factors for the i^{th} sample.

By proportionally allocating G to each SHAP value according to their global feature importance $I_j = \frac{1}{N}\sum_{i=1}^{N} |S_{ij}|$, which is the mean absolute SHAP value across all samples, we have $S'_{ij} = \frac{G \times I_j}{\sum_{j=1}^{6} I_j} + S_{ij}$, and finally we can have

$$\log B_i = \sum_{j=1}^{6} S'_{ij}.$$

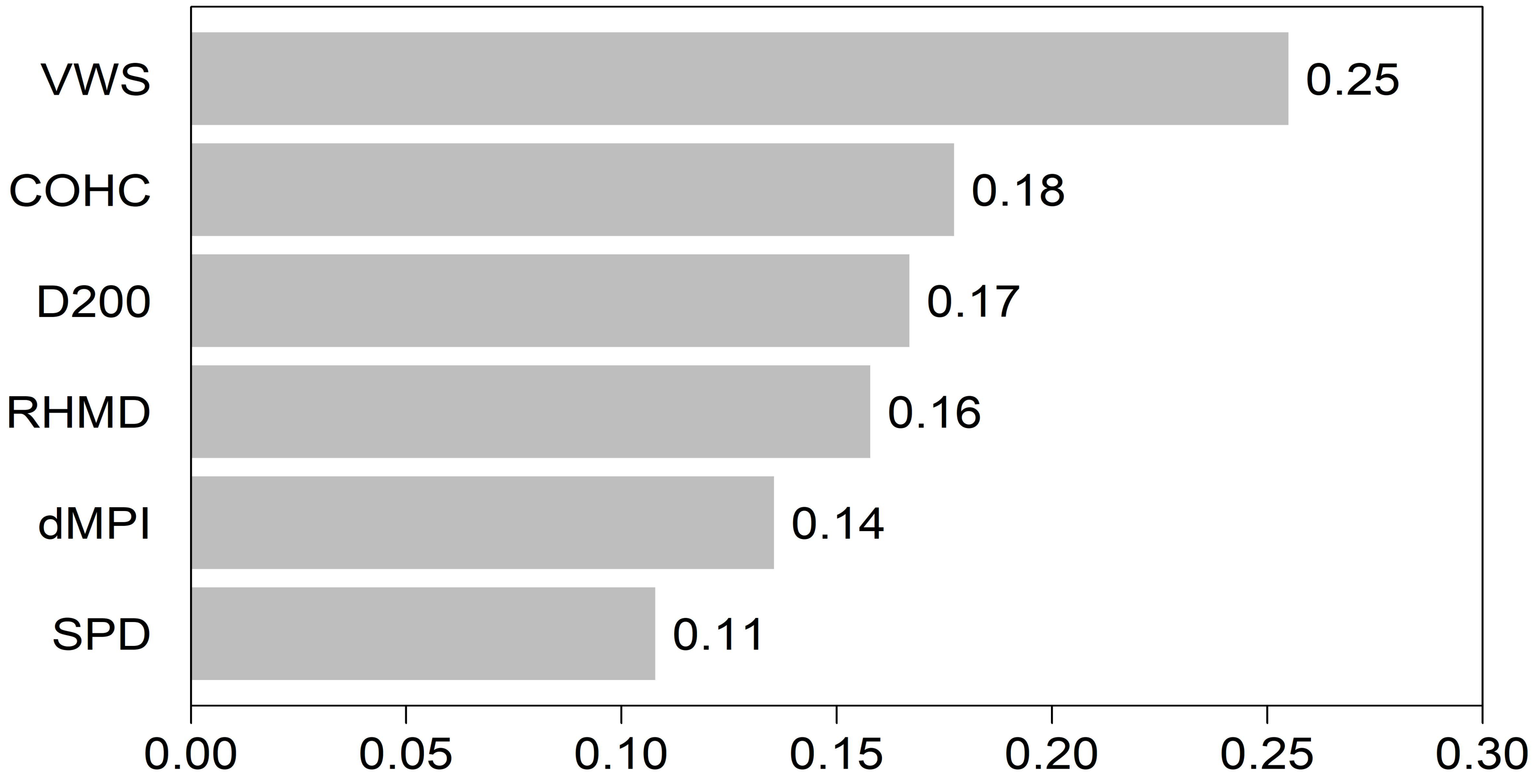
By definition, $S'_{ij} = \log(B_{ij})$, where $B_{ij} \in (0,1]$. We thus have

$$\log B_i = \sum_{j=1}^{6} \log(B_{ij}), \qquad B_i = \prod_{j=1}^{6} B_{ij}$$ for the i^{th} sample, namely a given time for a TC.

Similar to Bi, we can have Bij at a given time for a TC. With all samples, we can calculate the overall contribution of each of the environmental factors and thus get the relative importance of each environmental factor.

Xu, Wang, & Yang (2023)

Applications (1)
Quantifying environmental effects on TC intensity change

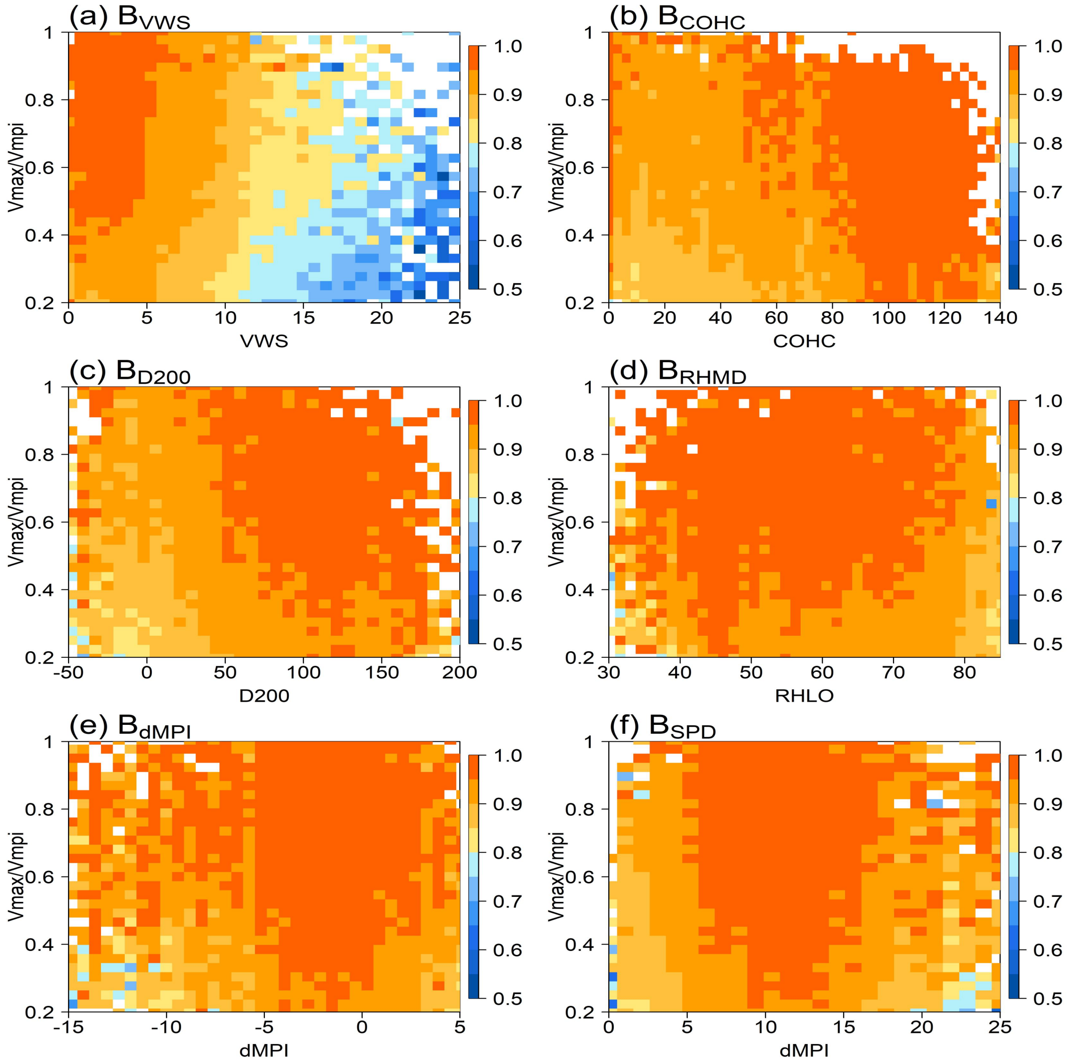


Relative importance of six individual environmental factors in the XGBoost model. Factors are given in a descending order of their relative importance

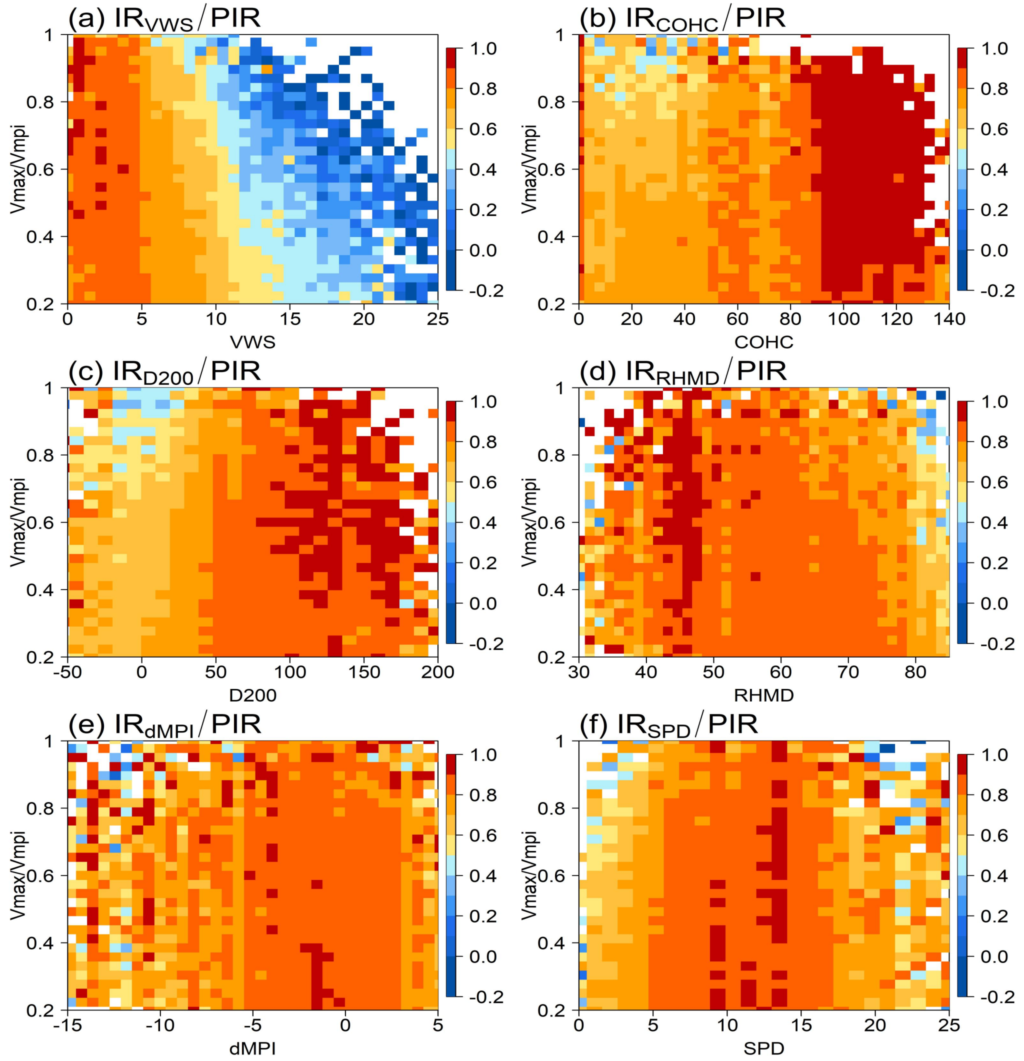
Xu, Wang, & Yang (2023)

Applications (1)
Quantifying environmental effects on TC intensity change

Contributions to B



Contributions to IR



Applications (2): Prediction of TC intensity

$$\frac{\partial V_{max}}{\partial \tau} = \frac{\alpha C_D}{h} V_{mpi}^2 \left[\boldsymbol{B} \left(\frac{V_{max}}{V_{mpi}} \right)^{3/2} - \left(\frac{V_{max}}{V_{mpi}} \right)^2 \right]$$

- ➢The key is to establish the relationship between ***B*** and environmental factors.
- ➢***B*** is a multiplication of all individual environmental ventilation parameters, and thus could not be determined by multiple regression method.
- ➢We combine the Bayesian hierarchical model (BHM) and neural network (NN) to determine ***B***.
  - NN: establish a latent process model to relate ***B*** with environmental factors, the neuron weights **W** needs to be deduced.
  - Likelihood (LH) can be calculated based on the V_{max} theory and data.
  - BHM： based on Bayes' rule, assume the prior $P(\mathbf{W}, V_{max})$, combine with the LH $P(data|\mathbf{W}, V_m)$, to obtain the posterior $P(\mathbf{W}, V_m|data)$

$$P(\mathbf{W}, V_m|data) \propto P(data|\mathbf{W}, V_m) \times P(\mathbf{W}, V_m)$$

- ➢A sample of **W** are drawn from the posterior distribution of **W** for prediction purpose.

Applications (2): Prediction of TC intensity

Flowchart

- At time *t*, we know $V_{max}(t)$ and all environmental factors, apply the sample of **W** to NN model to obtain the ensemble prediction of $B(t)$.
- Discretize the IR equation using $V_{max}(t)$、$V_{mpi}(t)$ and $B(t)$'s ensemble prediction

$$\Delta V_{max} = \frac{\alpha C_D}{h} V_{mpi}^2 \left[\boldsymbol{B} \left(\frac{V_{max}}{V_{mpi}} \right)^{3/2} - \left(\frac{V_{max}}{V_{mpi}} \right)^2 \right] \times \Delta\tau$$

Here ΔV_{max} is ensemble prediction and $\Delta\tau$ is time interval.

- At *t*+1， $V_{max}(t+1) \leftarrow V_{max}(t) + \overline{\Delta V_{max}}$， $\overline{\Delta V_{max}}$ is the ensemble mean.
- Go to the first step until the time of prediction.
- This is actually a Bayesian model averaging (BMA) approach. The results are much more robust than using any individually optimized NN model.

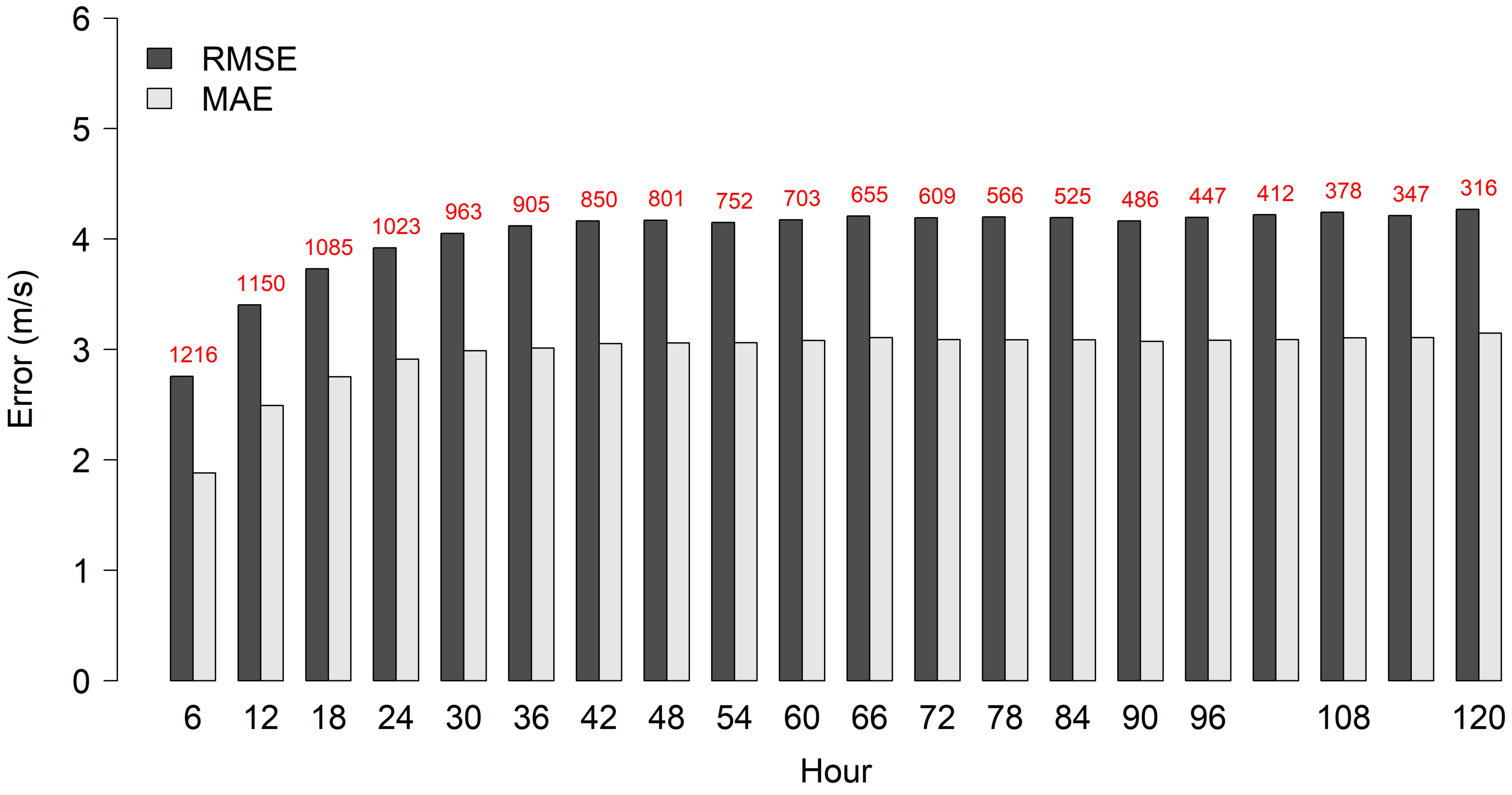
Applications (2): Prediction of TC intensity

Hindcasts of TCs over the North Atlantic during 2019-2021

- **Datasets:**
  - 6 hourly TC best-track data during 1982—2021; Environmental factors are from GFS reanalysis data from SHIPS dataset.
  - Training period: 1982—2018; Verification period: 2019—2021, 65 TCs.
- **NN model:**
  - Predictor: 66 altogether, including
    - 6 climatological persistence variables
    - 32 atmospheric dynamical factors
    - 28 atmospheric thermodynamic factors
  - Model structure: One hidden layer with 10 neurons (optimized).
  - Cases of neuron weights **W** from the posterior: $n = 100$.

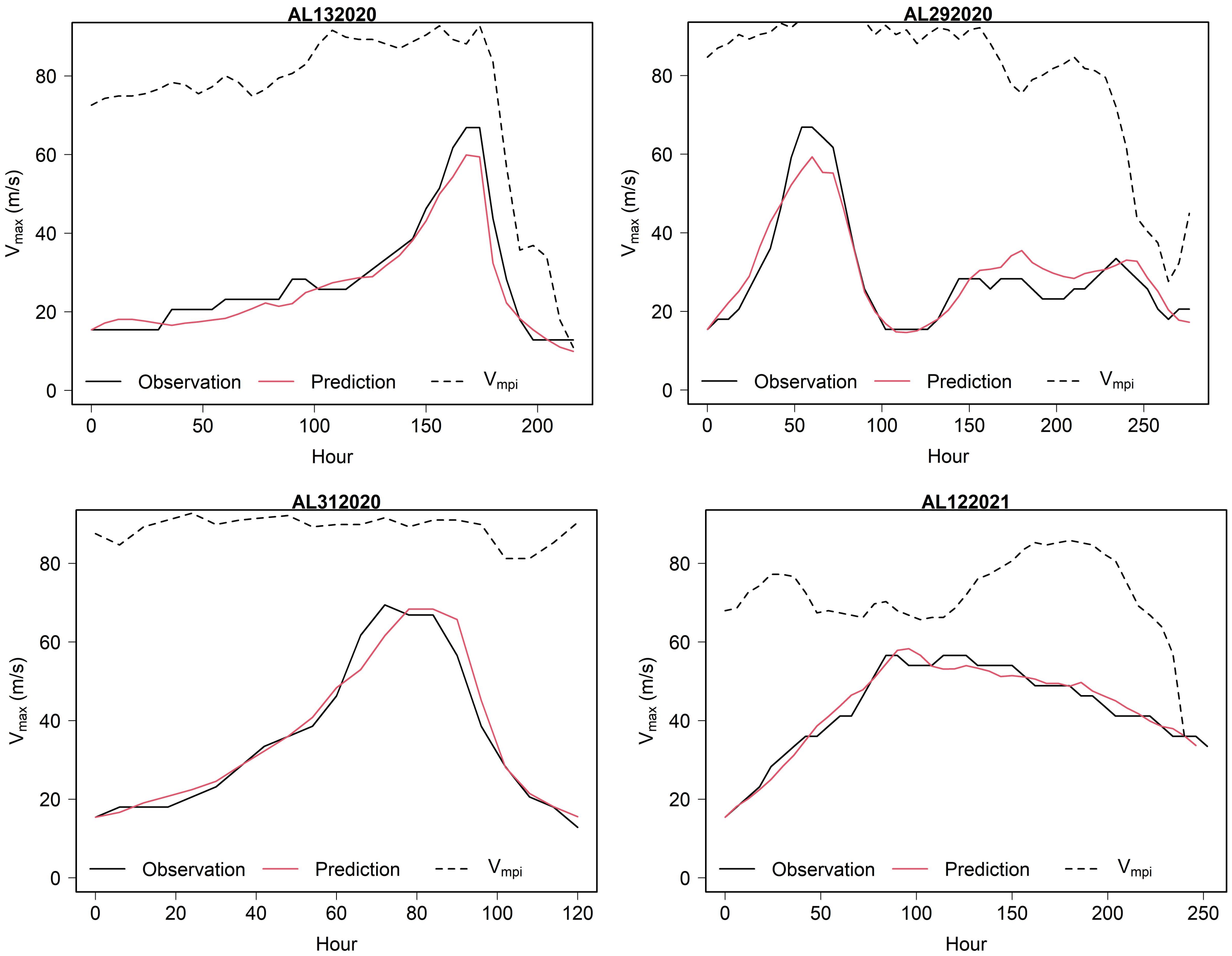
Applications (2): Prediction of TC intensity

Mean errors for 65 TCs over the North Atlantic during 2019-2021 hindcasts using GFS analysis and best-track data



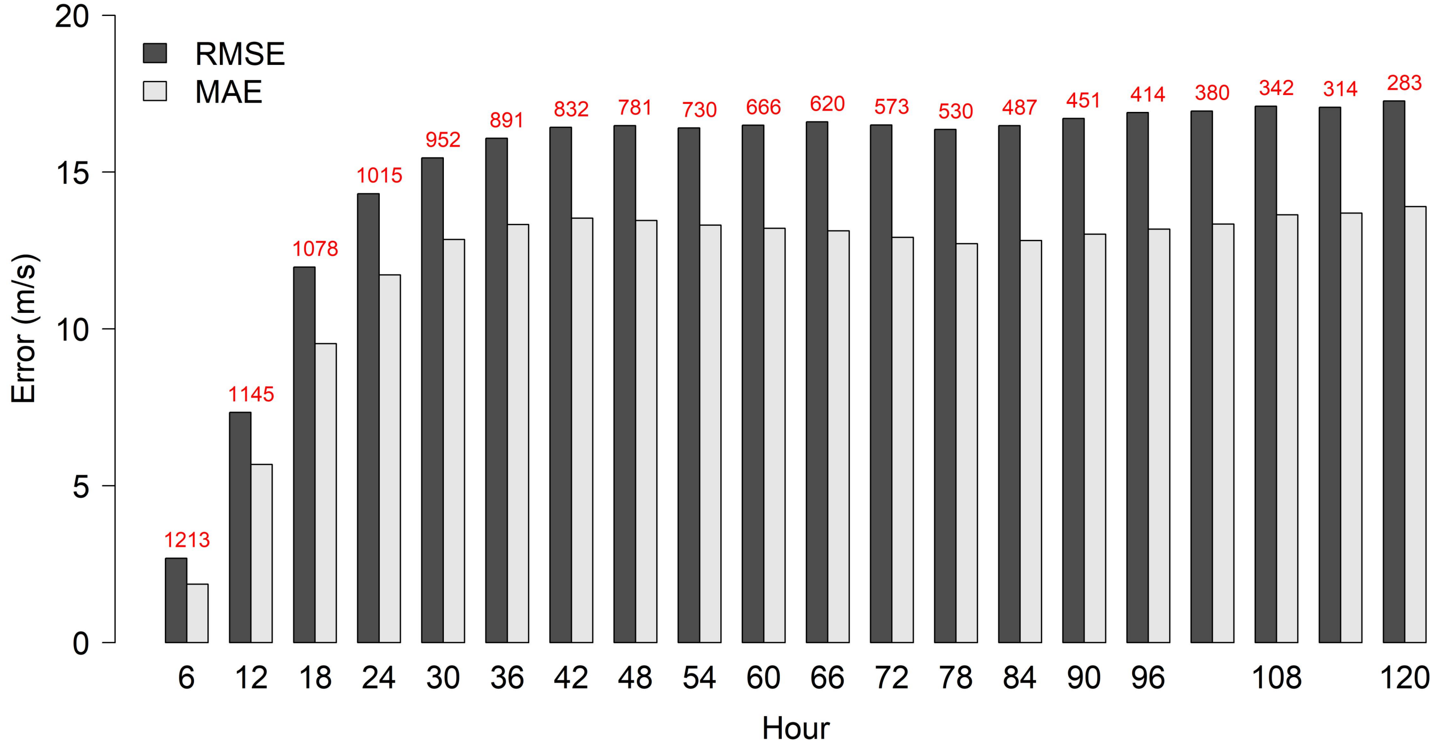
Applications (2): Prediction of TC intensity

Hindcast cases with GFS analysis & best-track data



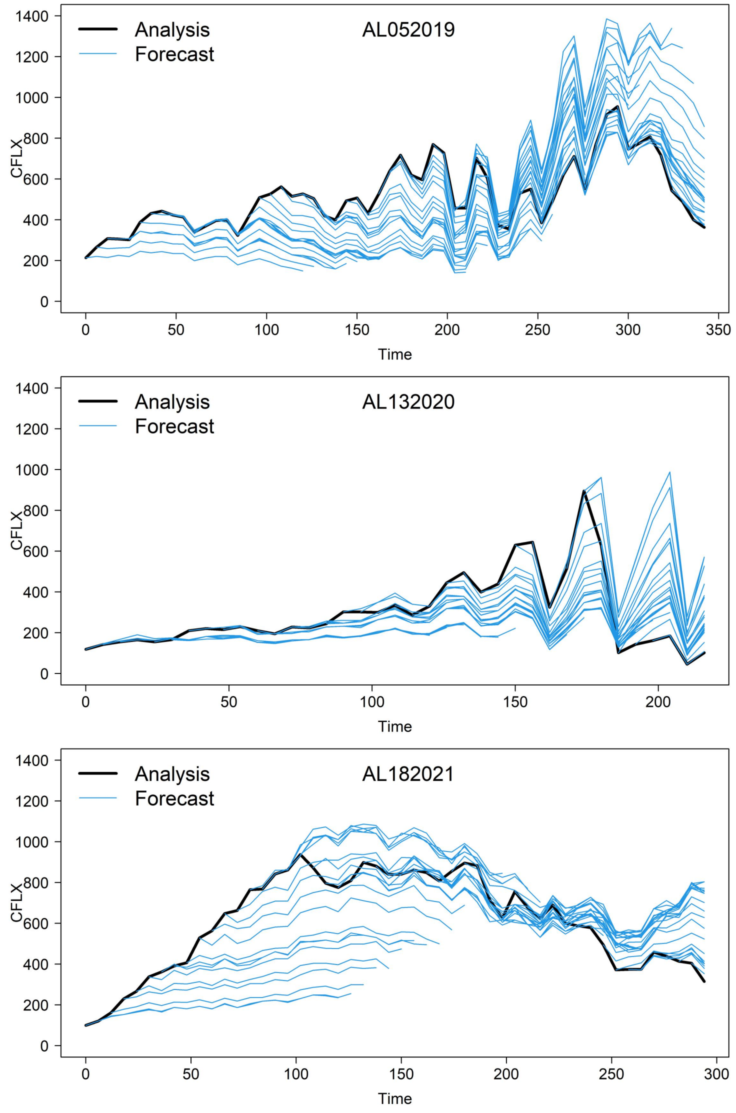
Applications (2): Prediction of TC intensity

Mean errors for the same 65 TCs but with GFS forecasts of track and environmental fields



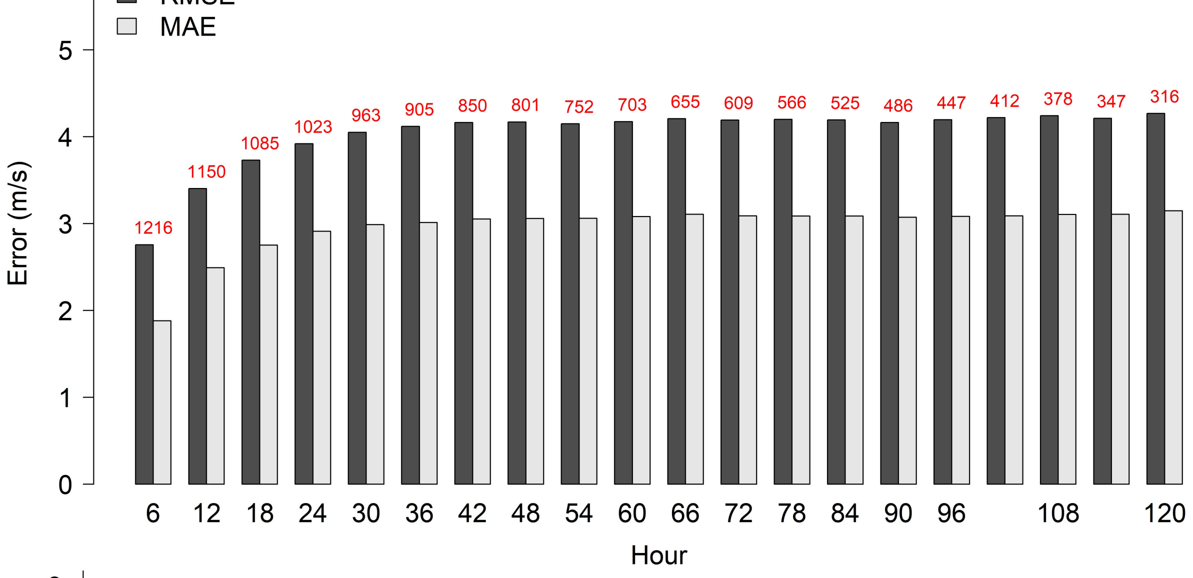
CFLX: Dry-air predictor based on the difference in surface moisture flux between air with the observed (GFS) RH value, and with RH of air mixed from 500 hPa to the surface, at the TC location

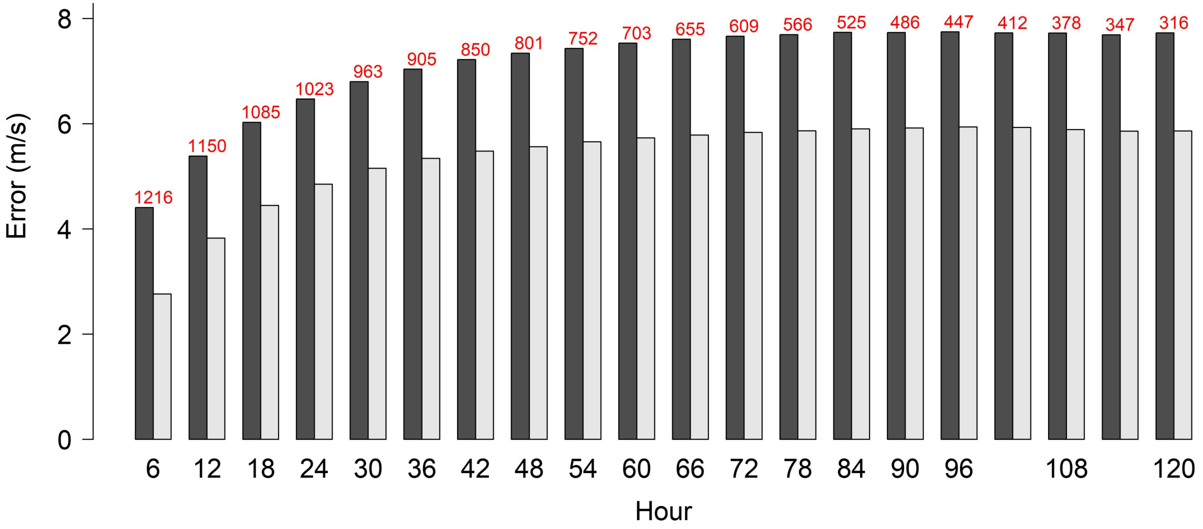
Main reasons: errors in track and factor forecasts, e.g., CFLX



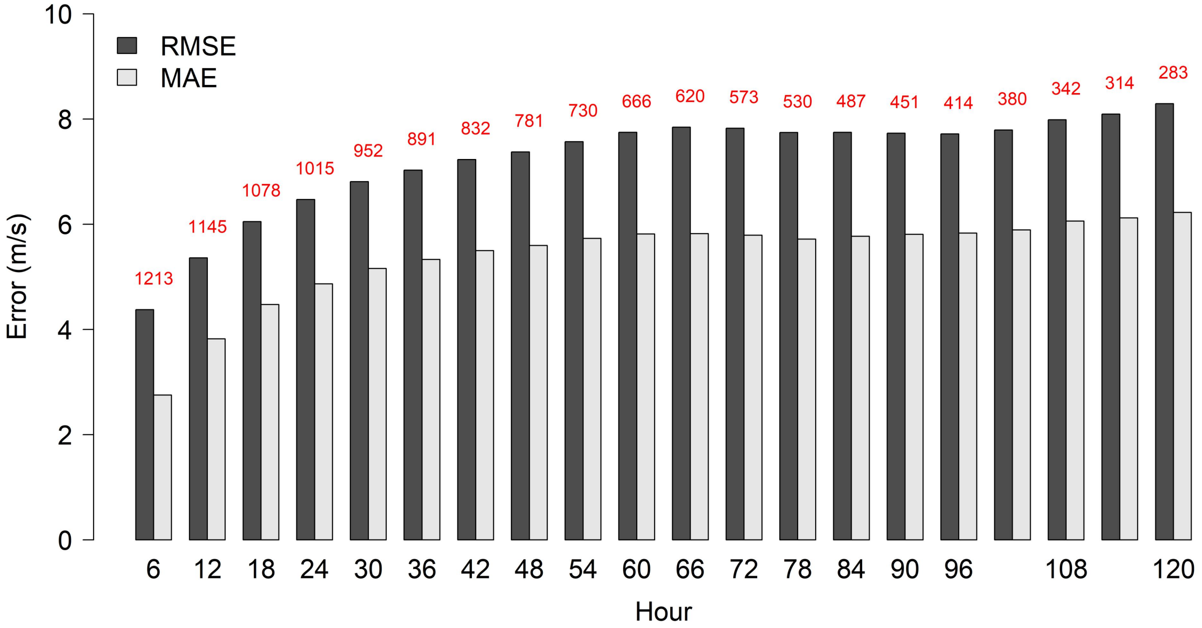
Applications (2): Prediction of TC intensity

The model was retrained without the use of CFLX



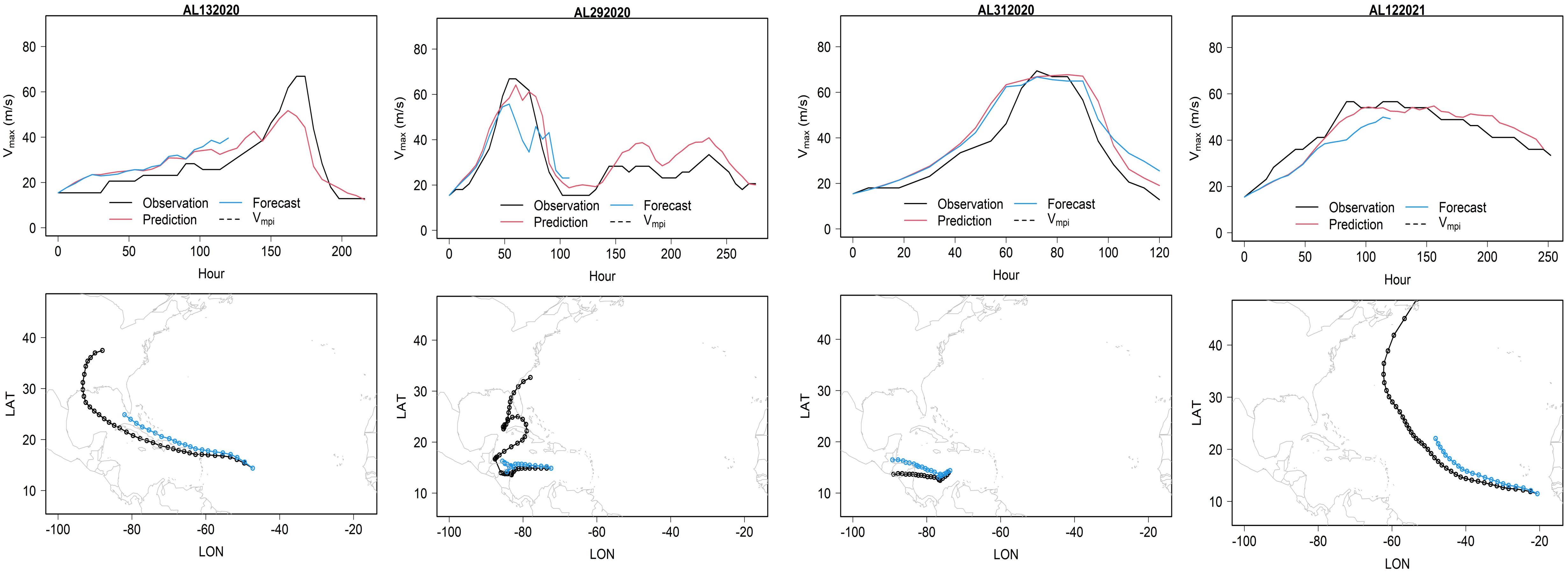


Mean errors for the same 65 TCs with GFS forecasts of track & environment



Applications (2): Prediction of TC intensity

Forecast cases with GFS forecasts of track and environmental factors (blue)
Also shown are intensity hindcasts with GFS analysis fields (red)



Outline

- Classic views on tropical cyclone (TC) intensification
- Early efforts toward time-dependent theories
- A unified time-dependent theory of TC intensification
- Applications:

  Quantifying environmental effects on TC intensity change

  Prediction of TC intensity

- **Future directions**

Future directions

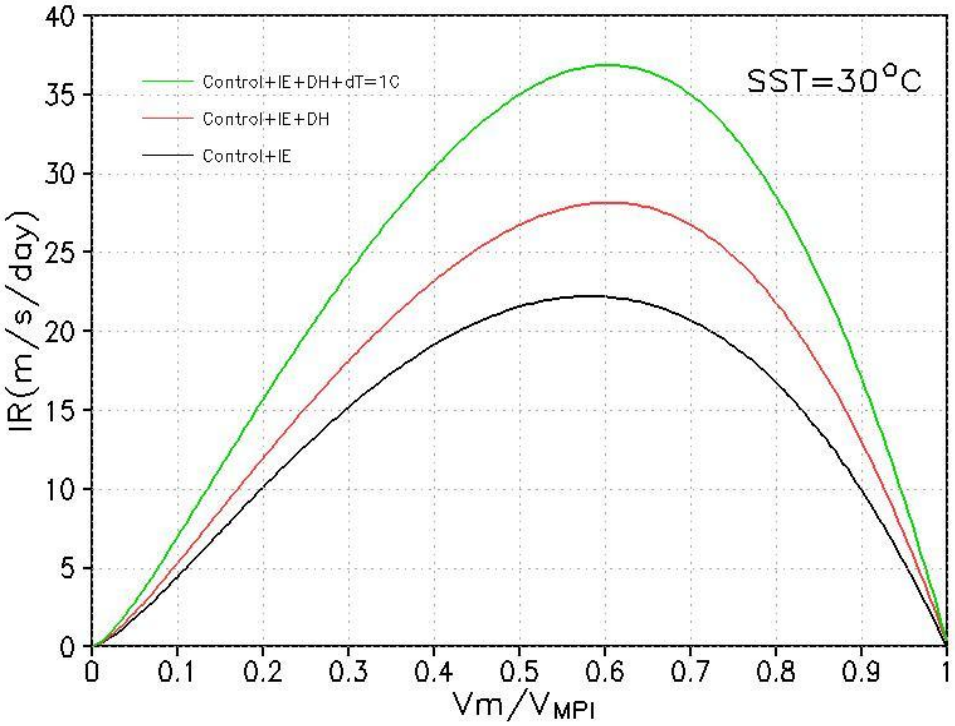
1. The maximum possible intensification rate (MPIR)

$$\frac{\partial V_{max}}{\partial \tau} = \frac{\alpha C_D}{h}\left\{AV_{MPI0}^2 - \left[1 - A\kappa - \gamma A\varepsilon\left(1 - \frac{\delta C_k}{2C_D}\right)\right]V_m^2\right\}$$

$$V_{MPI0}^2 = \frac{C_k}{C_D}\varepsilon\left[c_p(1+\mu)(T_s - T_a) + (1 - RH)\, L_v q_{vs0}^*\right]$$

$$\text{A} = \left(\frac{V_{max}}{V_{mpit}}\right)^{3/2}$$

Given the SST and environmental conditions, Ta and RH, we can estimate the MPIR when $A \approx 0.6$



Future directions

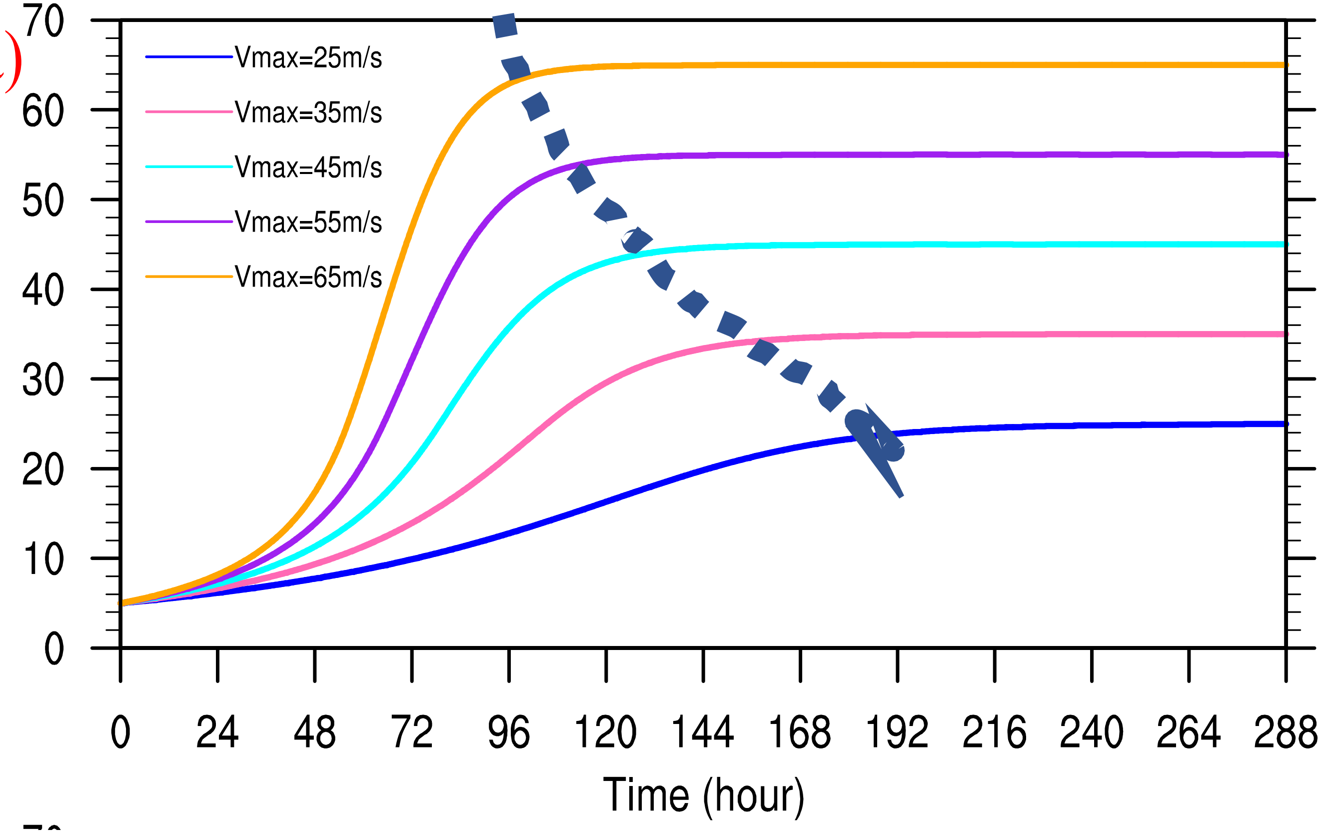
2. Long-term trends and global warming impacts

$$\frac{\partial V_{max}}{\partial \tau} = \frac{\alpha C_D}{h} V_{mpi}^2 \left[\boldsymbol{B} \left(\frac{V_{max}}{V_{mpi}} \right)^{3/2} - \left(\frac{V_{max}}{V_{mpi}} \right)^2 \right]$$

TC IR is proportional to the square of MPI GW will cause more RI?

Emanuel (2017)

(a)



TCs may become more intense and intensify more rapidly under global warming

Wang et al. (2023)

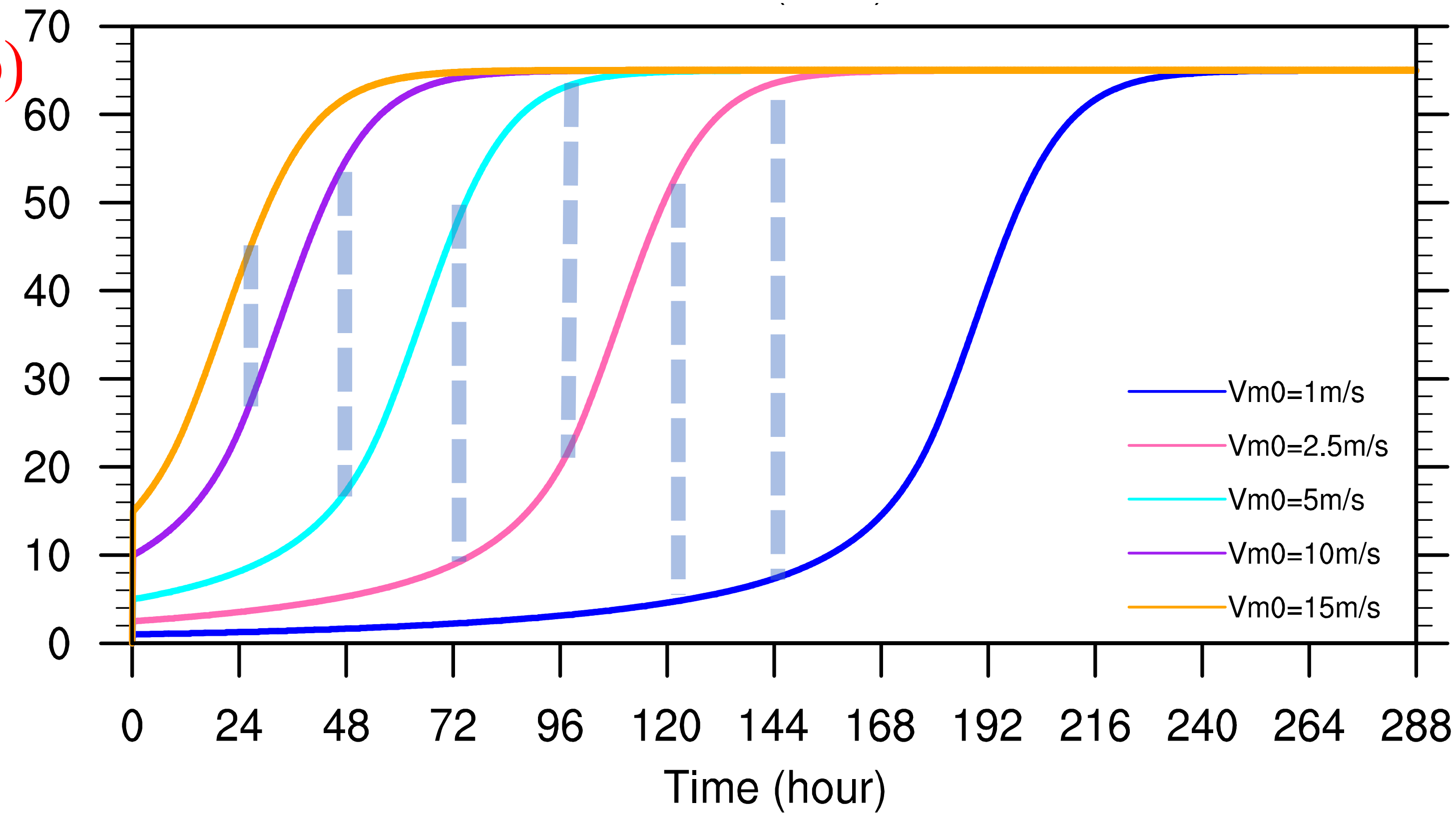
Future directions

3. Theoretical predictability of TC intensity

$$\frac{\partial V_{max}}{\partial \tau} = \frac{\alpha C_D}{h} V_{mpi}^2 \left[\boldsymbol{B} \left(\frac{V_{max}}{V_{mpi}} \right)^{3/2} - \left(\frac{V_{max}}{V_{mpi}} \right)^2 \right]$$

TC intensity prediction is very sensitive to initial intensity error

(b)



Error grows rapidly during RI stage but is originated from errors in the weak TC stage

Wang et al. (2023)

Future directions

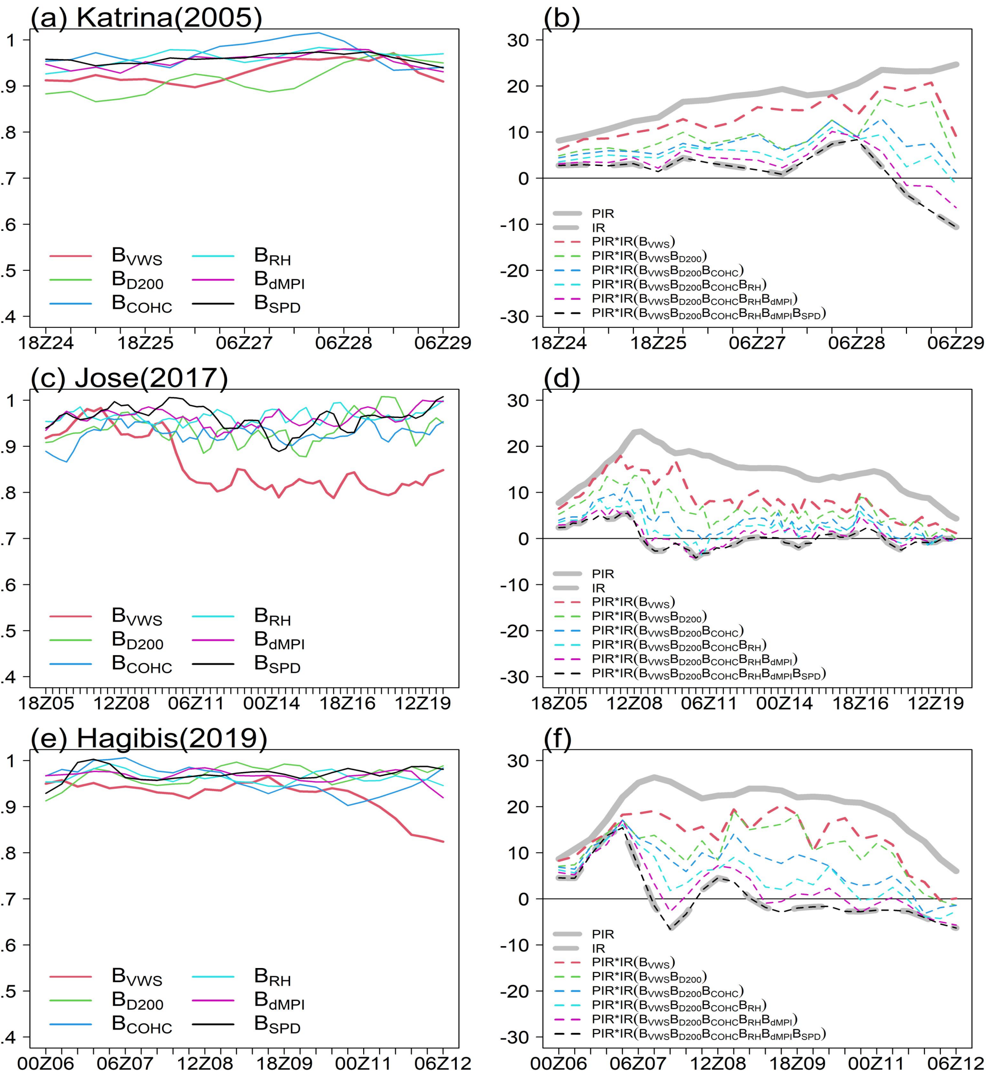
4. Understanding contributions by various factors to individual TCs

$$\frac{\partial V_{max}}{\partial \tau} = \frac{\alpha C_D}{h} V_{mpi}^2 \left[\boldsymbol{B} \left(\frac{V_{max}}{V_{mpi}} \right)^{3/2} - \left(\frac{V_{max}}{V_{mpi}} \right)^2 \right]$$

$$B_i = \prod_{j=1}^{6} B_{ij}$$

Different contributions of various environmental factors in different TC cases

Xu, Wang, & Yang (2023)



Mostly related publications

- **Wang, Y**., Y.-L. Li, J. Xu, Z.-M. Tan, and Y.-L. Lin, 2021a: The intensity-dependence of tropical cyclone intensification rate in a simplified energetically based dynamical system model. *J. Atmos. Sci.*, **78(7)**, 2033–2045, https://doi.org/10.1175/JAS-D-20-0393.1
- **Wang, Y**., Y.-L. Li, and J. Xu, 2021b: A new time-dependent theory of tropical cyclone intensification. *J. Atmos. Sci.*, **78(12)**, 3855–3865, https://doi.org/10.1175/JAS-D-21-0169.1
- Xu, J., and **Y. Wang**, 2022: Potential intensification rate of tropical cyclones in a simplified energetically based dynamical system model: An observational analysis. *J. Atmos. Sci.*, **79(4)**, 1045–1055, https://doi.org/10.1175/JAS-D-21-0217.1
- **Wang, Y**., J. Xu, and Z.-M. Tan, 2022: Contribution of dissipative heating to the intensity-dependence of tropical cyclone intensification. *J. Atmos. Sci.*, **79(8)**, 2169–2180; https://doi.org/10.1175/JAS-D-22-0012.1
- Liu, L., and **Y. Wang**, 2022: A physically based statistical model with the parameterized topographic effect for predicting the weakening of tropical cyclones after landfall over China, *Geophys. Res. Lett.*, **49(17)**, e2022GL099630, https://doi.org/10.1002/2021GL099630
- **Wang, Y**., Z.-M. Tan, and Y.-L. Li, 2023: Some refinements to the most recent simple time-dependent theory of tropical cyclone intensification and sensitivity. *J. Atmos. Sci.*, **79(1)**, 321–335, https://doi.org/10.1175/JAS-D-22-0135.1
- Xu, J., **Y. Wang**, and C. Yang, 2023: Quantifying the environmental effects on tropical cyclone intensity change using a simple dynamically based dynamical system model. *J. Atmos. Sci.,* (in press).
- Li, Y.-L., **Y. Wang**, and Z.-M. Tan, 2023: Why does no size parameter appear in the recent time-dependent theory of tropical cyclone intensification? *J. Atmos. Sci.*, (revised)

Thank you for your attention!

Any questions or comments?