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A Machine Learning Assisted Development of a Model for the Population Dynamics of Clouds

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Introduction





Science Questions:

- I. What are the processes the govern the evolution of the population of convective cells?
- 2. How can these processes be modelled and represented in global models?

Objectives

To develop a model of non-equilibrium dynamics of cloud populations for:

- Testing hypotheses regarding the roles of various physical processes and
- Parameterizing the spectrum of convective clouds (from isolated to MCSs) in a unified framework.

Background

A brief history of the problem



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1970

General energy cycle

(Arakawa and Schubert 1974)

Paths followed since

Quasi-equilibrium assumption



Mass flux





1990

2000

2010

 Bulk and spectral finite deviation from quasi-equilibrium (Pan and Randall 1998, Yano and Plant 2010)
 Stochastic variations about quasi-equilibrium

(Craig and Plant 2008, Wagner and Graf 2010)

Prognostic, stochastic cloud population models

(Plant 2012, Hagos et al. 2018)



Observational data and definitions

12 winters of C-Pol Radar reflectivity data at Darwin



Stainer et al. (2005) algorithm is used to identify convective cells and stratiform areas.

The model





After Arakawa and Schubert (1974)

- The next state is some function of the current state and the change in convective area fraction.
- Convective mass flux per cell depends on cell size.
- The growth rate of stratiform area is some function of convective cells and decays exponentially in the absence of active convection.

1. Machine learning algorithm for deteriming f_c and f_s



 W_{c0}

 W_{c1} b_{c0}

 b_{c1}

Training Algorithm Optimized Convective data f_c $X_{c} = [s_{(t)}, c_{(t)}]$ $a_{c0}^{t} = RELU(Z_{c0}^{t}) \Longrightarrow Z_{1}^{t} = a_{0}^{t} \cdot W_{c1} + b_{c1}$ $Z_{c0}^{t} = X_{c} \cdot W_{c0} + b_{c0}$ $dA_c = A_c(t + dt) - A_c(t)$ $\boldsymbol{c}_{(t+dt)}^{predicted} = RELU(Z_1^t) \cdot dA_c + \boldsymbol{c}_{(t)}$ $c_{(t+dt)}^{true}$ $OBJ_{c} = norm(\mathbf{c}_{(t+dt)}^{predicted} - \mathbf{c}_{(t+dt)}^{true})$ Stratiform Optimized Training Algorithm \mathbf{f}_{s} data W_{s0} $\Rightarrow Z_0^t = \boldsymbol{c}_{(t)} \cdot W_{s0} + b_{s0} \Rightarrow a_{s0}^t = RELU(Z_{s0}^t)$ $f_s^{\text{predicted}} = a_{s0}^t \cdot W_{s1} + b_{s1}$ $\boldsymbol{c}_{(t)}$ W_{s1} $OBJ_s = norm(f_s^{predicted} - f_s^{true})$ f_s^{true} b_{s0} b_{s1}

The machine learning code is written in TensorFlow[™]

The algorithm is trained by half of the 150,000 cases of observed transitions.

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0.00

10

Convective area fraction

0

15

20

1. Machine learning Validation of f_c: Convective clouds

Hereafter the model will be referred to as "machine

Learning Assisted Model for Population of clouds (LAMP)".



The algorithm predicts the convective cell size distribution and its diurnal cycle reasonably well.

5

log 10(freguency)

0.00

10

Convective area fraction

5

0

15

20

1. Machine learning Validation of f_s (Stratiform area)





Given convective cell sizes the algorithm represents stratiform area distribution and it diurnal cycle well.

1. Machine learning Interpretation: Convective clouds



Convictive cells vs convective area fraction

(stratiform feedback off)



The effect of stratiform feedback

SIZe

G



- At low cloud fraction the number of cells grows rapidly.
- At larger area fraction the size of cells grows rapidly.
- Stratiform area favors formation of new smaller cells



1. Machine learning Interpretation: Stratiform area





The growth rate of stratiform area is approximately linearly related to convective area.

▶ it is relatively insensitive to the size distribution.

2. Mass Flux Relationship with Convective Cell Sizes



Why do we care about cell size distribution anyway?





Because larger cells carry more than their share of mass flux.

$$M_b = \boldsymbol{c} \cdot \boldsymbol{m}_b$$

From Hagos et al. 2018 (JAMES) 11

3. The Model (a) Linear



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$M_b = \boldsymbol{c} \cdot \boldsymbol{m}_b$ independent of cell size \boldsymbol{c} (constant)



Smaller mass flux per-cell delays the diurnal cycle of total mass flux because larger cells are required.

Larger cells then lead to larger stratiform area.

3. The Model: Non-linear (b) Response to constant forcing



 $M_{b} = \boldsymbol{c} \cdot \boldsymbol{m}_{b}$ m_b dependent of cell size \boldsymbol{c}



Non-linearity leads to oscillation in mass flux.

Stratiform feedback damps the oscillation by favoring smaller convective cells.

3. The Model: Non-linear (b) Response to diurnally varying forcing



(a) Diurnal Cycle of Convective Area fraction Stratiform Feedback Off Stratiform Feedback On 6000 Convective area (*km*²) 5000 4000 3000 2000 1000 3AM 6AM 9AM 12PM 3PM 6PM 9PM Time (hr) (c) Diurnal Cycle of Mass Flux Mass flux per domain area ($kgm^{-2}s^{-1}$) Forcing 0.06 Stratiform Feedback Off Stratiform Feedback On 0.04 0.02 3AM 6AM 9AM 12PM 3PM 6PM 9PM Time (hr)



Stratiform feedback leads to smaller cells
The mass flux then requires larger total convective area.

Resulting larger stratiform area.



Summary

Formation of large stratiform areas (i.e MCS like feature)



Furthermore

- The diurnal cycle of convection in a non-equilibrium framework is sensitive to mass flux per unit convective cell area.
- low-frequency variability of large-scale forcing favors larger stratiform area.
- Future work: A parameterization based on this framework will be tested in a climate model after the similar analyses are performed over other regions.