

# Rainfall nowcasting using Burgers' equation

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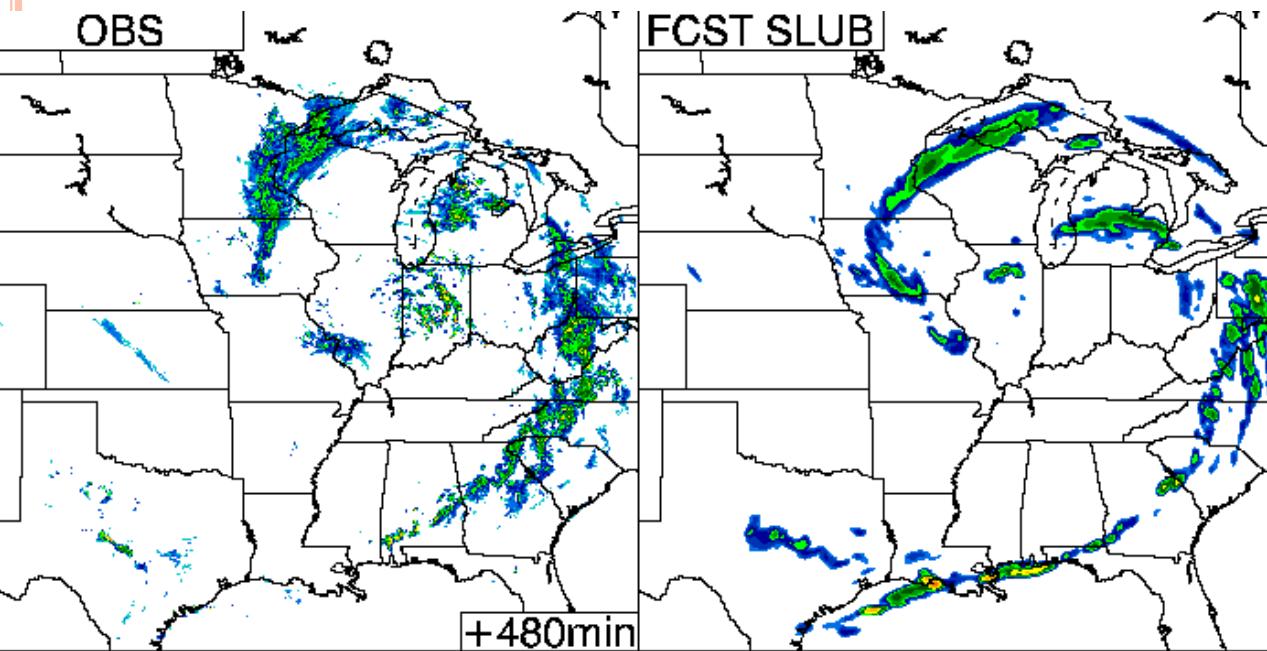


# RADAR-BASED NOWCASTING

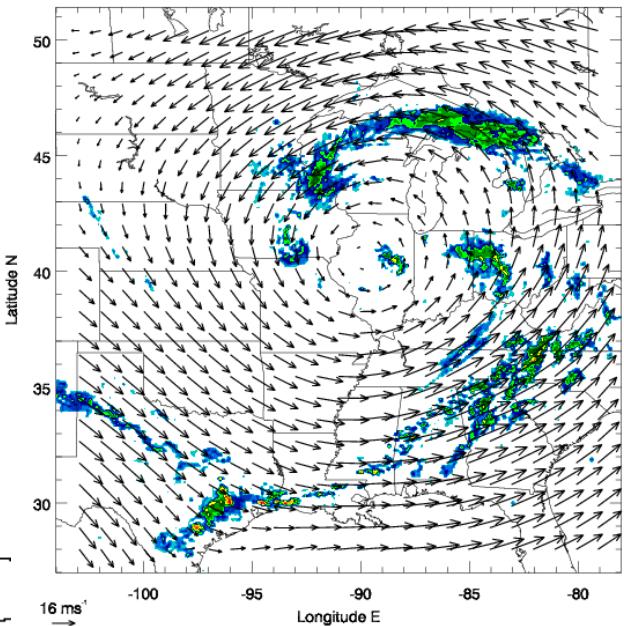
Ex) MAPLE

1. Motion fields of precip.  
(Variational Echo Tracking: VET)

3. Verification  
(compare fcst w/ obs)



2. Advect precip. fields:  
Semi-Lagrangian backward



$$\hat{R}(t_0 + \tau, \vec{x}) = R(t_0, \vec{x} - \vec{\alpha})$$

↑  
Predicted field      ↑  
Observed field

- Growth/decay (scale of predictability)
- Non-stationary motion fields

Germann and Zawadzki (2002)

# METHODOLOGY

Lagrangian extrapolation (advection)     $\hat{R}(t_0 + \tau, \vec{x}) = R(t_0, \vec{x} - \alpha)$

OR

Conservation equation

$$\frac{dR}{dt} = \frac{\partial R}{\partial t} + u \frac{\partial R}{\partial x} + v \frac{\partial R}{\partial y} = 0$$

We solved this simple advection equation(AE) directly

$$\frac{\partial R}{\partial t} = -u \frac{\partial R}{\partial x} - v \frac{\partial R}{\partial y} \quad : \text{Type 1}$$

Add diffusion term for spatial filtering (smoothing):  
advection diffusion equation (ADE)

$$\frac{\partial R}{\partial t} = -u \frac{\partial R}{\partial x} - v \frac{\partial R}{\partial y} + v \left( \frac{\partial^2 R}{\partial x^2} + \frac{\partial^2 R}{\partial y^2} \right) \quad : \text{Type 2}$$



## METHODOLOGY

However, above two equations assume that the motion vector field is **stationary in time** (constant motion vectors for entire forecast time)

Introduce Burgers' equation:

$$\frac{\partial u}{\partial t} = -u \frac{\partial u}{\partial x} - v \frac{\partial u}{\partial y} + s \left( \frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial y^2} \right)$$
$$\frac{\partial v}{\partial t} = -u \frac{\partial v}{\partial x} - v \frac{\partial v}{\partial y} + s \left( \frac{\partial^2 v}{\partial x^2} + \frac{\partial^2 v}{\partial y^2} \right)$$

to allow non-stationarity of motion vectors. The  $s$  controls the degree of the smoothness.

# METHODOLOGY

Semi-Lagrangian extrapolation (**S-L**):  $\hat{R}(t_0 + \tau, \vec{x}) = R(t_0, \vec{x} - \alpha)$

Type 1: advection equation(AE)

$$\frac{\partial R}{\partial t} = -u \frac{\partial R}{\partial x} - v \frac{\partial R}{\partial y}$$

Type 2: advection diffusion equation(ADE)

$$\frac{\partial R}{\partial t} = -u \frac{\partial R}{\partial x} - v \frac{\partial R}{\partial y} + v \left( \frac{\partial^2 R}{\partial x^2} + \frac{\partial^2 R}{\partial y^2} \right)$$

Type 3: advection equation(AE) + Burgers' equation

$$\frac{\partial R}{\partial t} = -u \frac{\partial R}{\partial x} - v \frac{\partial R}{\partial y} +$$

$$\begin{aligned}\frac{\partial u}{\partial t} &= -u \frac{\partial u}{\partial x} - v \frac{\partial u}{\partial y} + s \left( \frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial y^2} \right) \\ \frac{\partial v}{\partial t} &= -u \frac{\partial v}{\partial x} - v \frac{\partial v}{\partial y} + s \left( \frac{\partial^2 v}{\partial x^2} + \frac{\partial^2 v}{\partial y^2} \right)\end{aligned}$$

Type 4: advection diffusion equation(ADE) + Burgers' equation

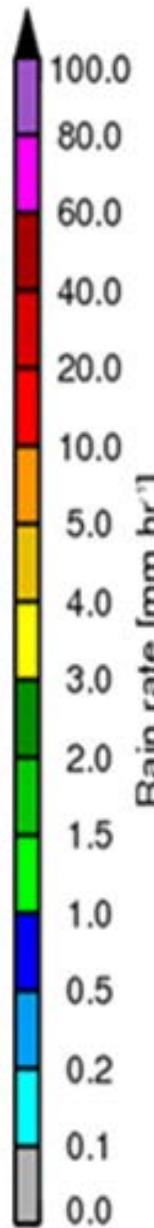
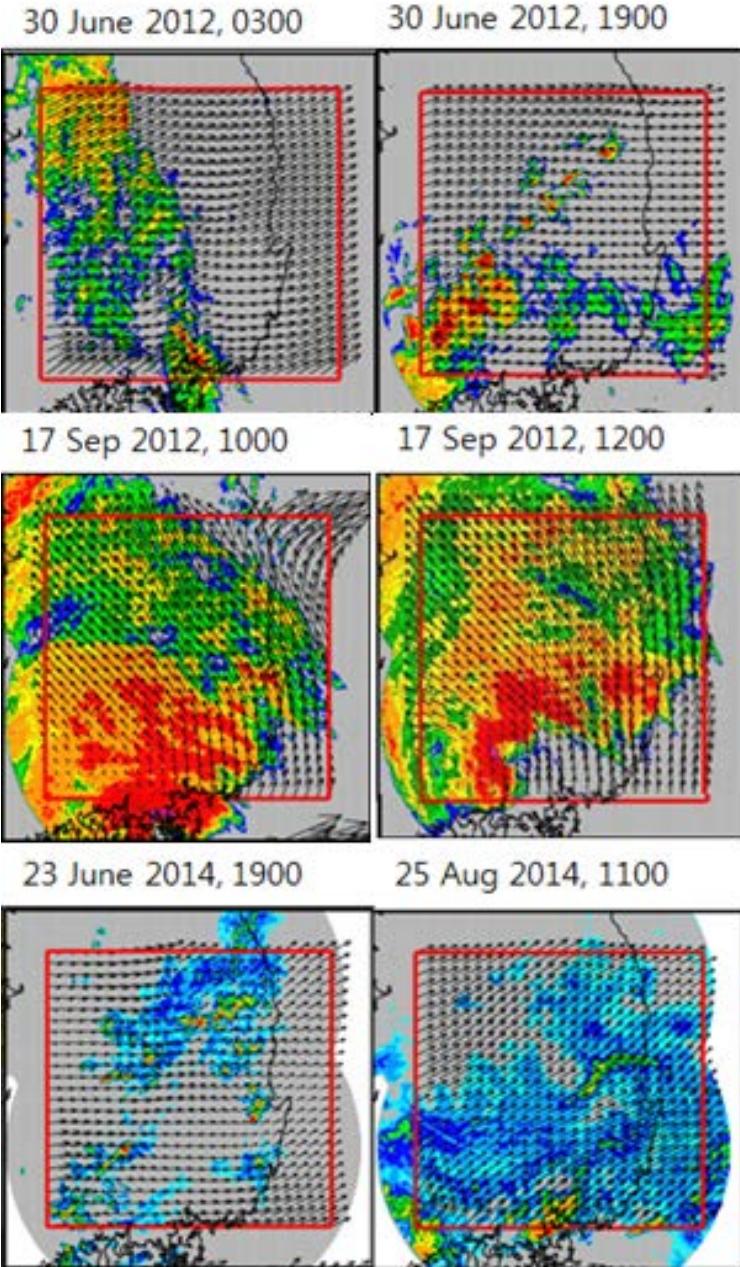
$$\frac{\partial R}{\partial t} = -u \frac{\partial R}{\partial x} - v \frac{\partial R}{\partial y} + v \left( \frac{\partial^2 R}{\partial x^2} + \frac{\partial^2 R}{\partial y^2} \right) +$$

$$\begin{aligned}\frac{\partial u}{\partial t} &= -u \frac{\partial u}{\partial x} - v \frac{\partial u}{\partial y} + s \left( \frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial y^2} \right) \\ \frac{\partial v}{\partial t} &= -u \frac{\partial v}{\partial x} - v \frac{\partial v}{\partial y} + s \left( \frac{\partial^2 v}{\partial x^2} + \frac{\partial^2 v}{\partial y^2} \right)\end{aligned}$$

# METHODOLOGY

1. Motion vectors ( $u, v$ ): derived from variational echo tracking (VET) with  $\Delta t = 2.5$  min
2. Advection (diffusion) equation:
  - ODE for time: Explicit (forward) Runge-Kutta fourth order (RK4) with  $\Delta t = 0.1$  min
  - Spatial derivative for R: Finite difference method with  $\Delta x = \Delta y = 0.25$  km
  - $0.0 \leq v \leq 0.1$
3. Burgers' equation:
  - Spatial derivative for  $(u, v)$ : Finite difference method with  $\Delta x = \Delta y = 10$  km
  - $s = 0.2$

# DATA



## 1. Cases

- 6 events, 2.5 min CAPPI composite from 3 radars
- 15 min nowcasting up to 3h

## 2. Computation domain

- Southeast area in South Korea
- **312 km x 312 km** at 0.25 km resolution (**1248 x 1248 pixels**)
- Motion vectors : 10 km resolution
- Verification domain: **250 km x 250 km** (red box)

# SKILL SCORES, ERROR STATISTICS

## ❖ 2D Contingency table

	Forecast	
Obs	$R \geq R_{th}$	$R < R_{th}$
$R \geq R_{th}$	Hit (a)	Miss (c)
$R < R_{th}$	False alarm (b)	Correct negative (d)

## ❖ Categorical scores

Verification score	Formula
Probability of detection ( <b>POD</b> )	$a/(a+c)$
False alarm ratio ( <b>FAR</b> )	$b/(a+b)$
Critical success index ( <b>CSI</b> )	$a/(a+b+c)$
Equitable threat score ( <b>ETS</b> )	$(a-w)/(a+b+c-w)$ , $w=(a+b)(a+c)/(a+b+c+d)$

## ▪ Correlation coefficient :

$$r(t) = \frac{\sum_{n(t)} (R_0(t)R_F(t))}{\left(\sum_{n(t)} (R_0)^2 \sum_{n(t)} (R_F)^2\right)^{1/2}},$$

## ▪ Mean Absolute Error : $MAE(t) = \frac{1}{n(t)} \sum_{n(t)} |R_F(t) - R_O(t)|$

## ▪ Conditional Mean Absolute Error : $CMAE(t) = \frac{1}{a(t)} \sum_{a(t)} |R_F(t) - R_O(t)|$

# MAPLE vs. AE + DIFFUSION

0300 LST  
30 June 2012

Observation

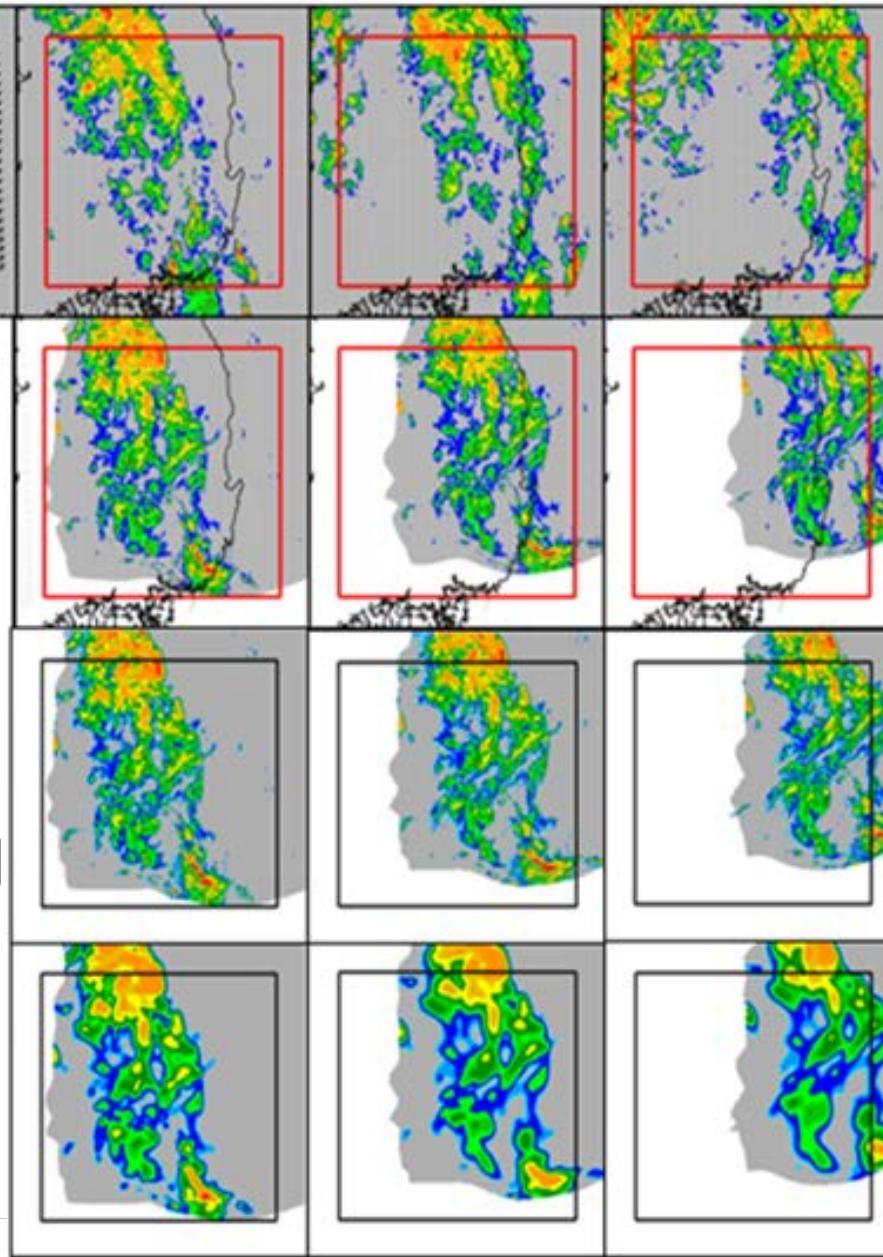
+0.0 min      +60.0 min      +120.0 min      +180.0 min

Forecast

MAPLE

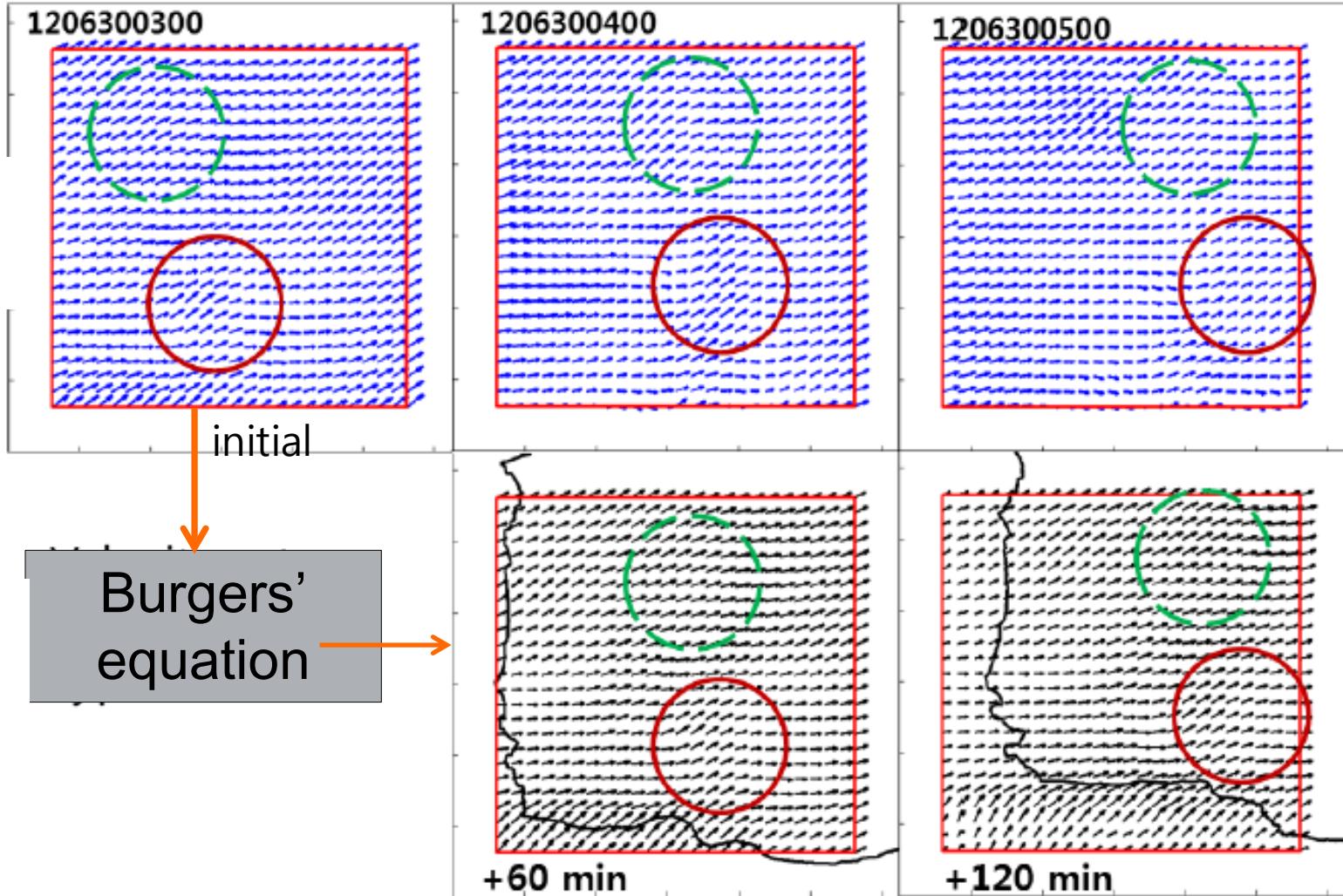
Type 1  
Advection eq

Type 2  
Advection eq +  
diffusion( $\nu=0.05$ )

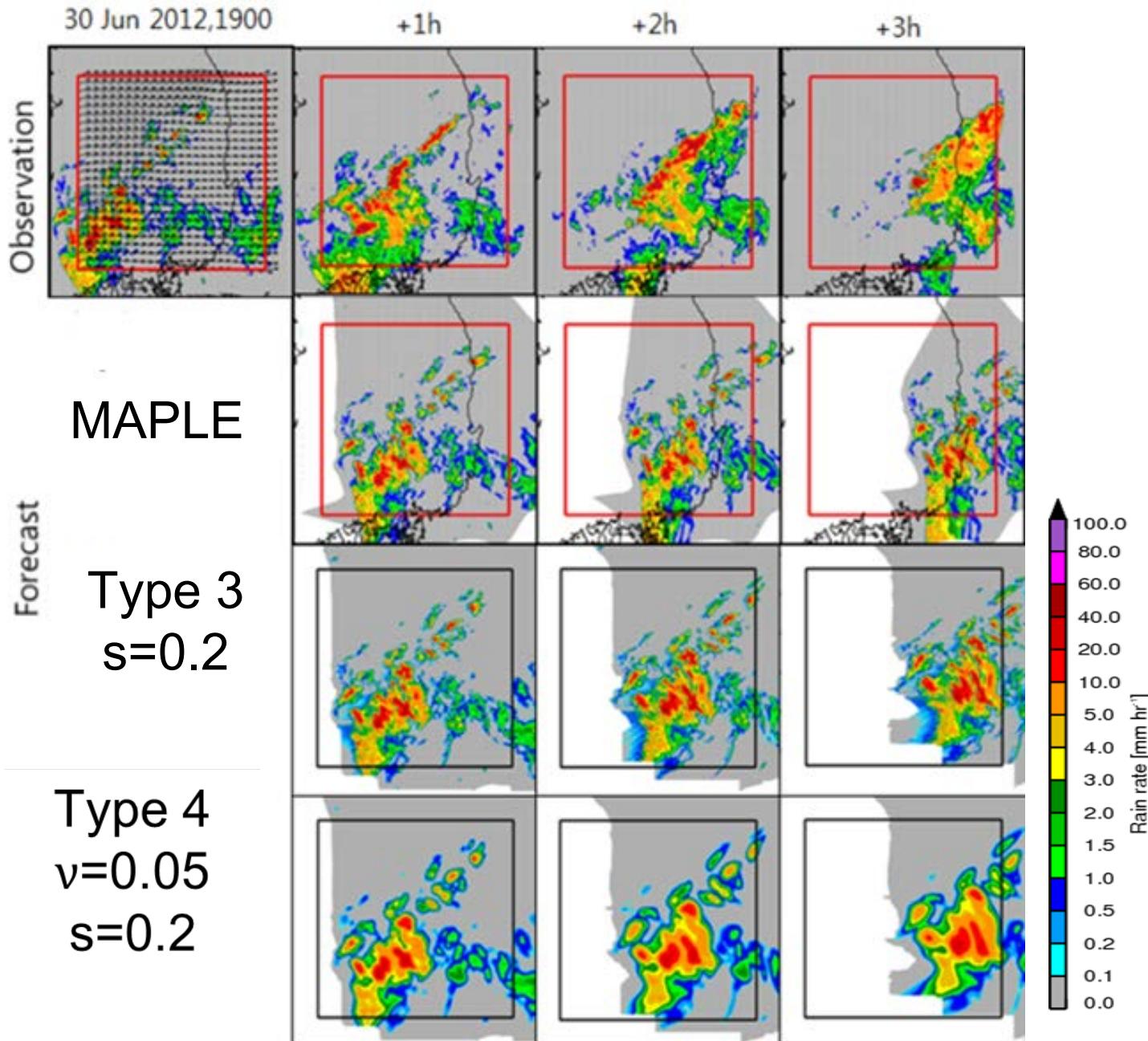


# NON-STATIONARY MOTION VECTORS

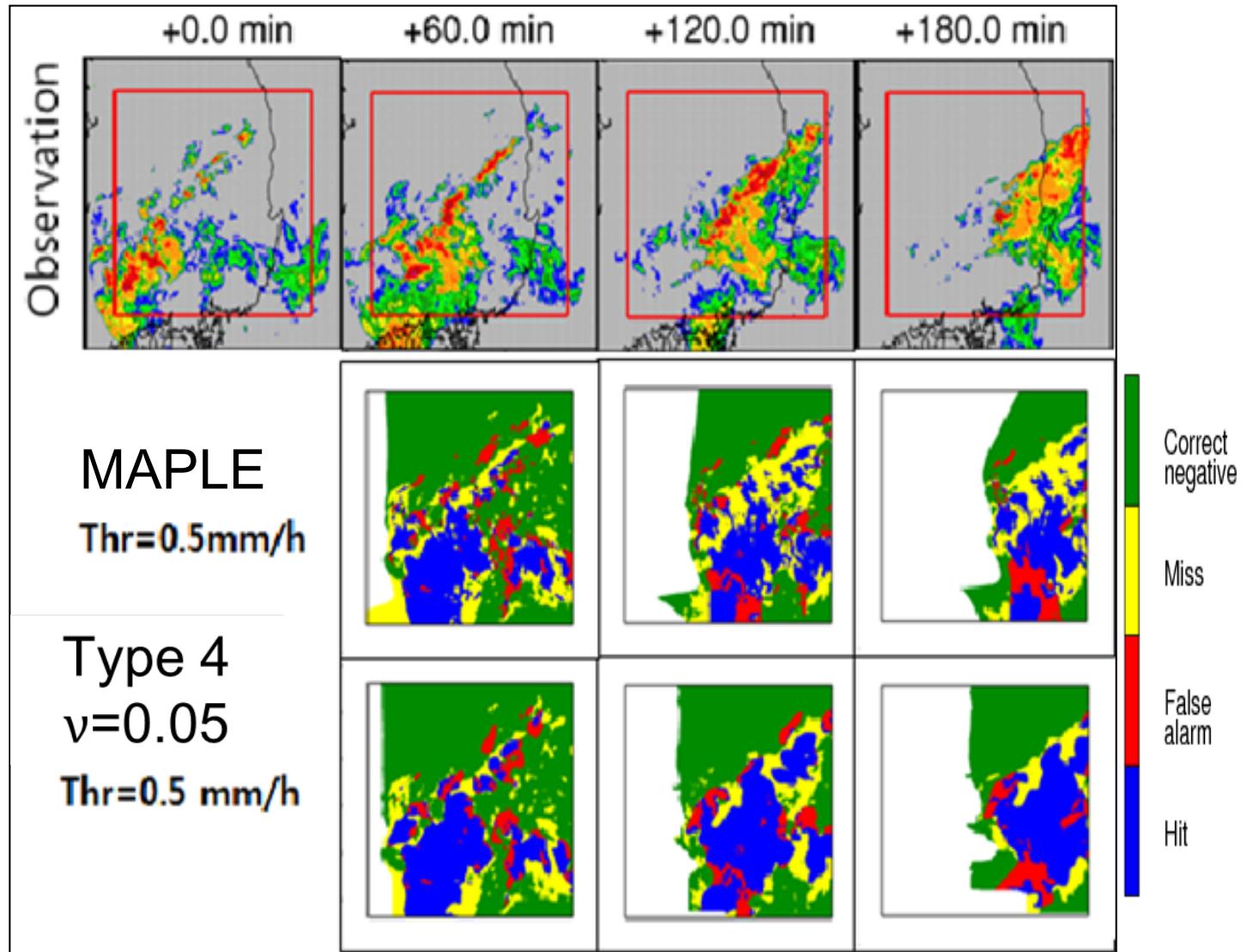
VET  
w/ OBS



# MAPLE vs. AE + NON-STATIONARY + DIFFUSION

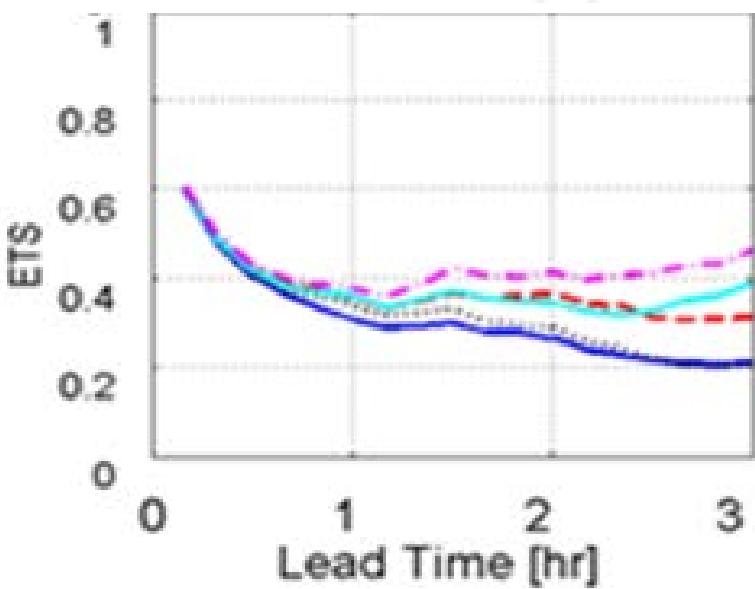
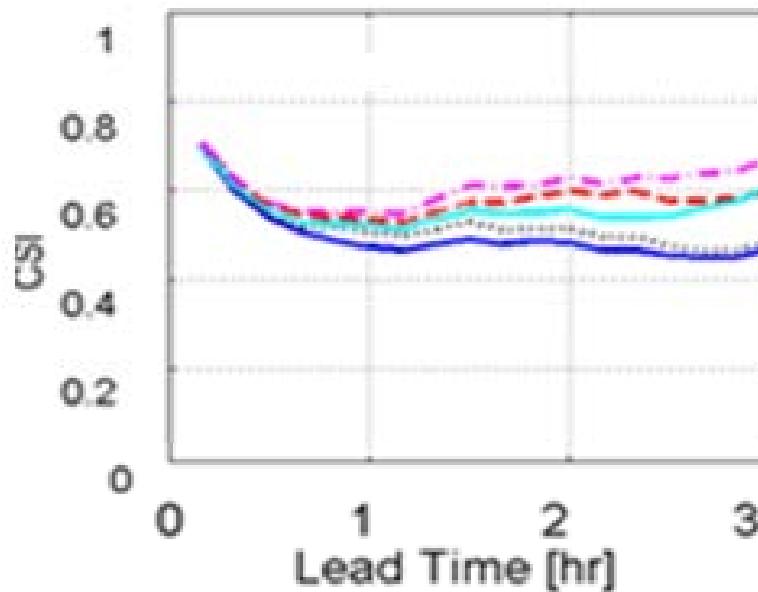
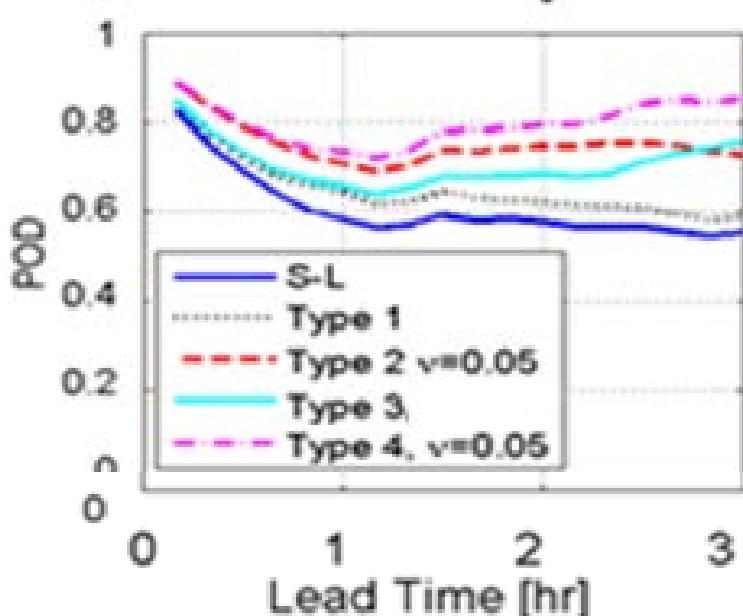


# MAPLE vs. AE + NON-STATIONARY + DIFFUSION



# MAPLE vs. AE + NON-STATIONARY + DIFFUSION

Skill scores  $R_{th} = 0.1\text{mm/h}$



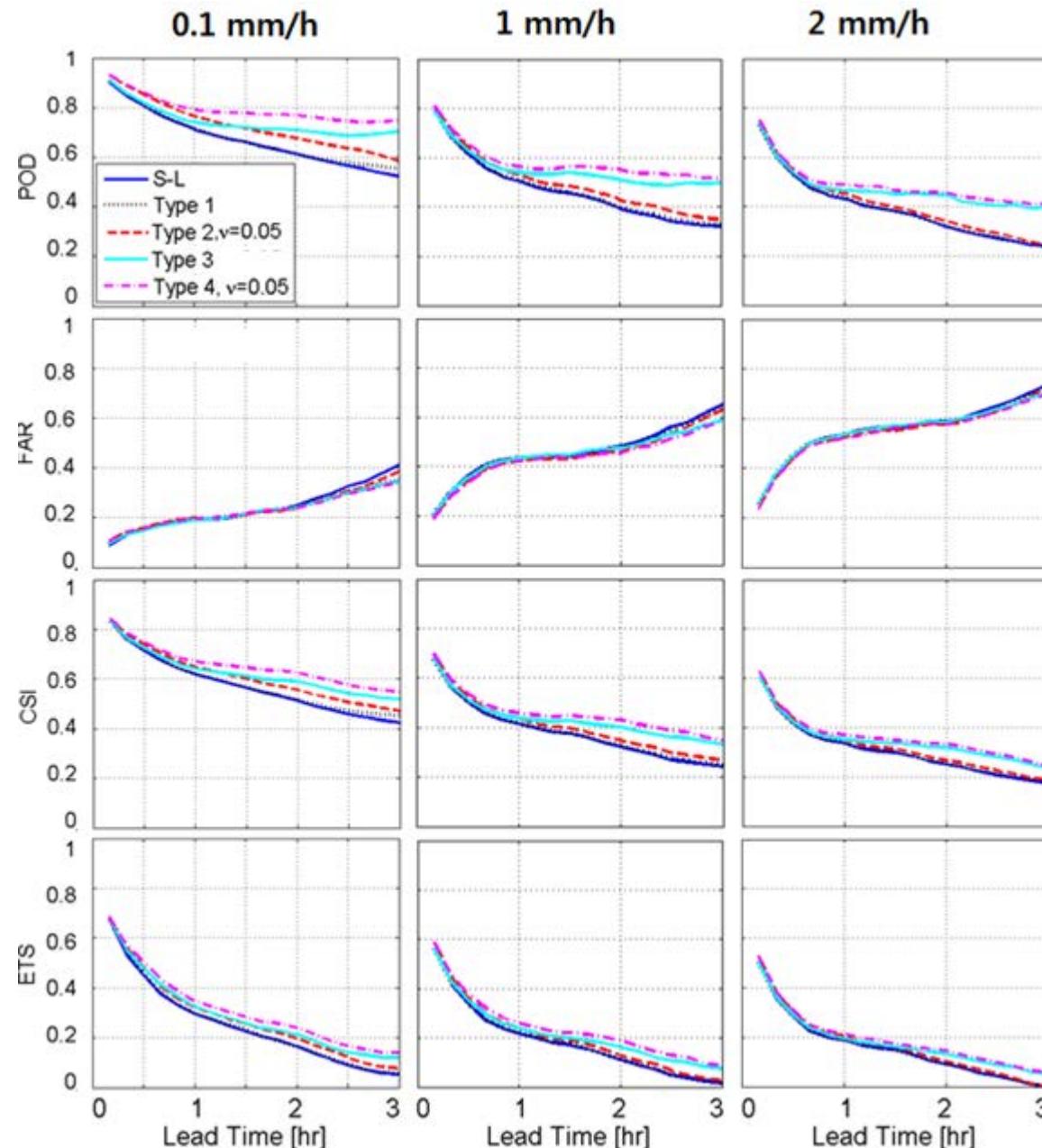
Type 4

MAPLE



# MAPLE vs. AE + NON-STATIONARY + DIFFUSION

Average skill  
scores: 6 events

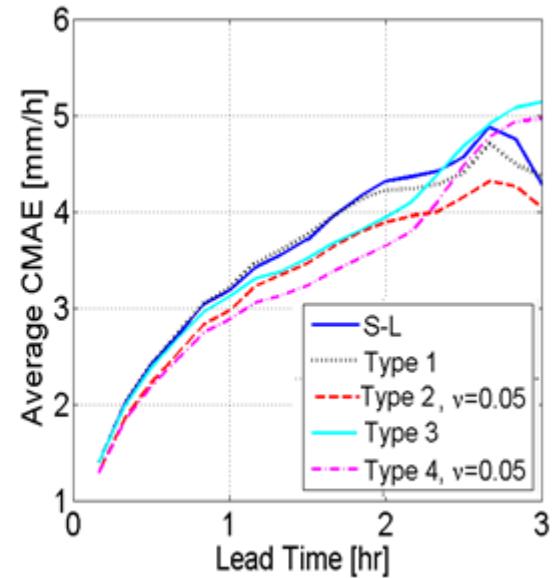
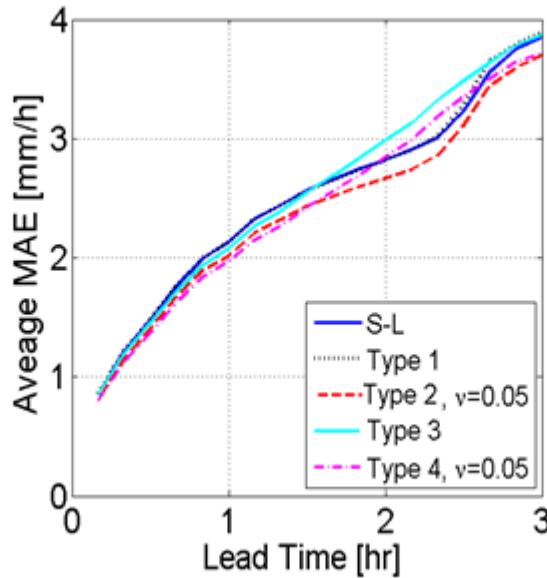
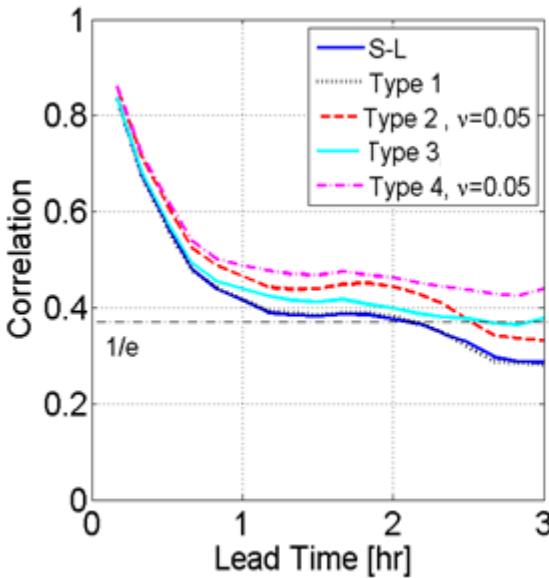


“Type 3, 4”



# MAPLE vs. AE + NON-STATIONARY + DIFFUSION

Average skill scores: 6 events



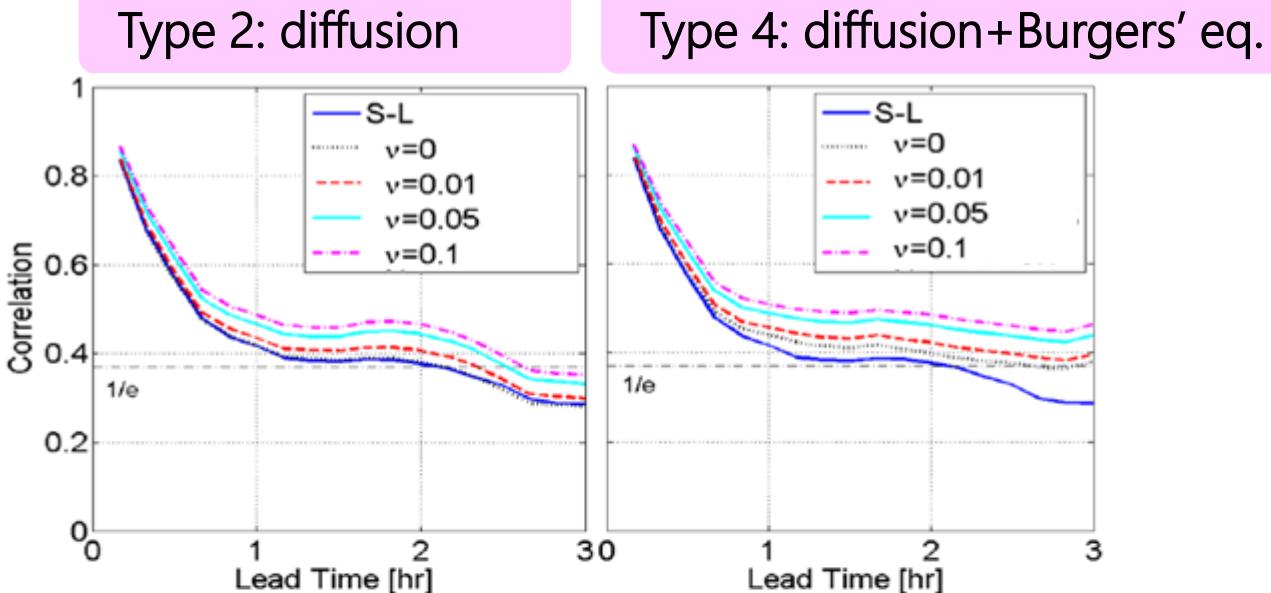
- Lifetime : Type 4(  $>3\text{h}$ ) > Type 3 (around 3h) > Type 2 (2.5h) > MAPLE (2h) = Type 1



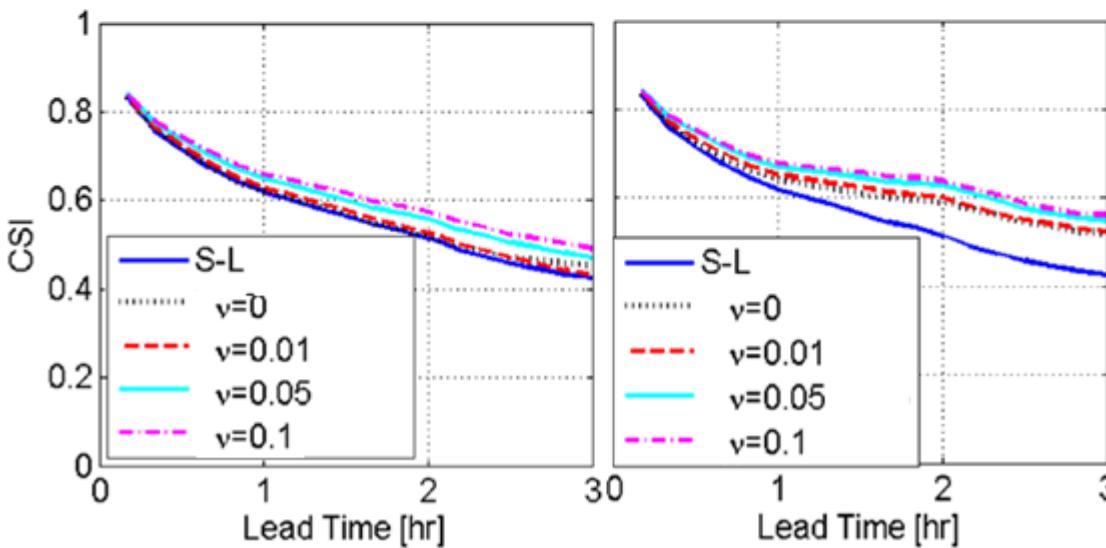
# MAPLE vs. AE + NON-STATIONARY + DIFFUSION

## Sensitivity to diffusion

Average correlation



Average CSI



## NON-STATIONARY MOTION VECTORS

Matrix norm  $\|\nabla \cdot u\|$ ,  $u(x,y,0)$  is obtained from VET  
and  $u(x,y,t)$  is from 2D Burgers' equations

Start	30 Jun 2012,	30 Jun 2012,	17 Sep 2012,	17 Sep 2012,	23 Jun 2014,	25 Aug 2014,
Lead time	0300	1900	1000	1200	1900	1100
+0 h	2.01	1.07	5.13	3.08	0.92	1.22
+1 h	2.55	1.05	3.20	2.41	0.89	1.24
+2 h	2.86	1.38	3.12	1.98	0.86	1.18
+3 h	2.35	1.87	2.54	2.25	0.85	1.18
Variance	0.13	0.15	1.27	0.22	0.00	0.00

$$\text{Var}(\|\nabla \cdot u\|) > 0.13$$

# NON-STATIONARY MOTION VECTORS

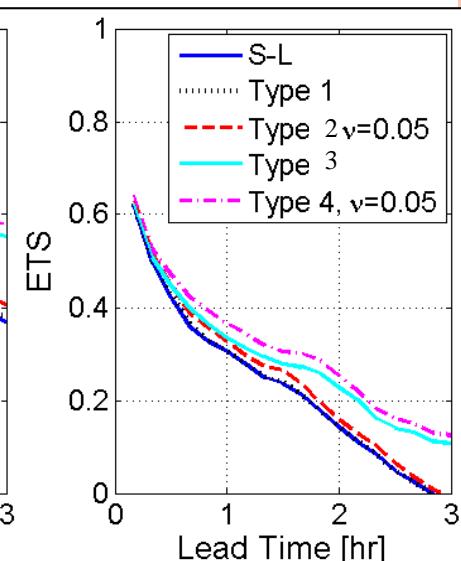
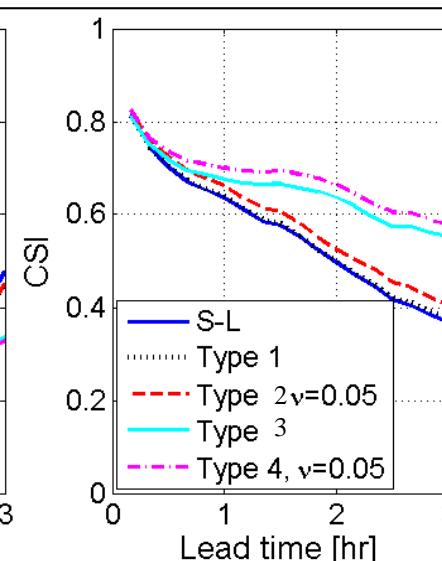
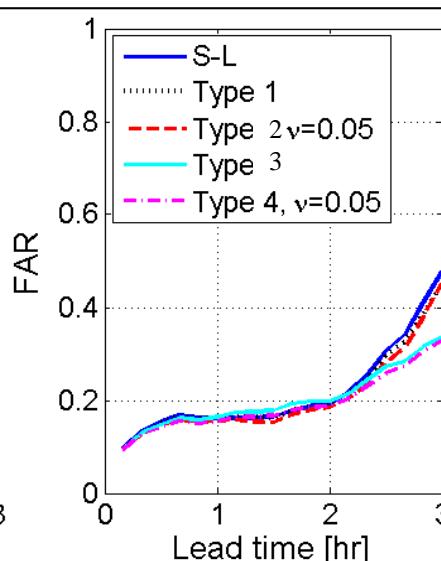
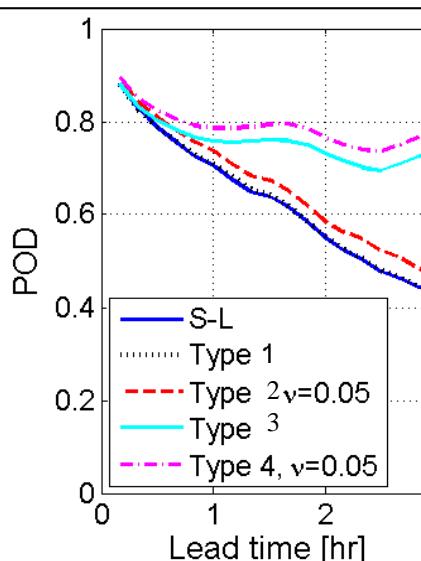
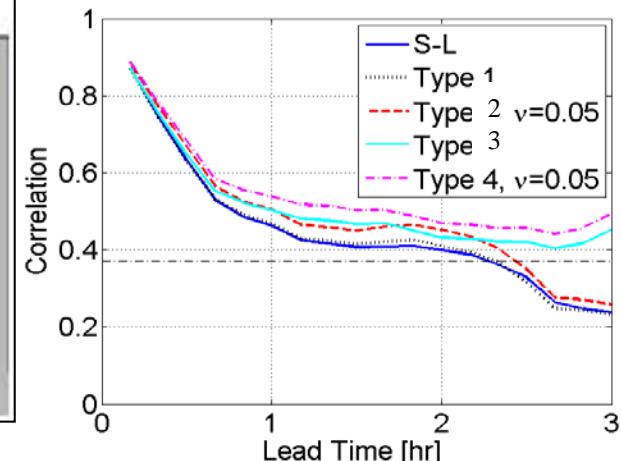
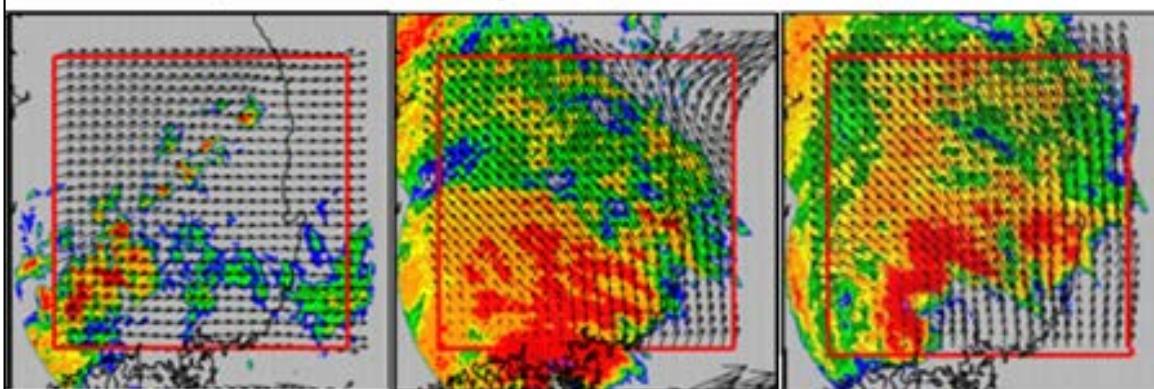
$$\text{Var}(\|\nabla \cdot \mathbf{u}\|) > 0.13$$

← Non-stationarity?

30 June 2012, 1900

17 Sep 2012, 1000

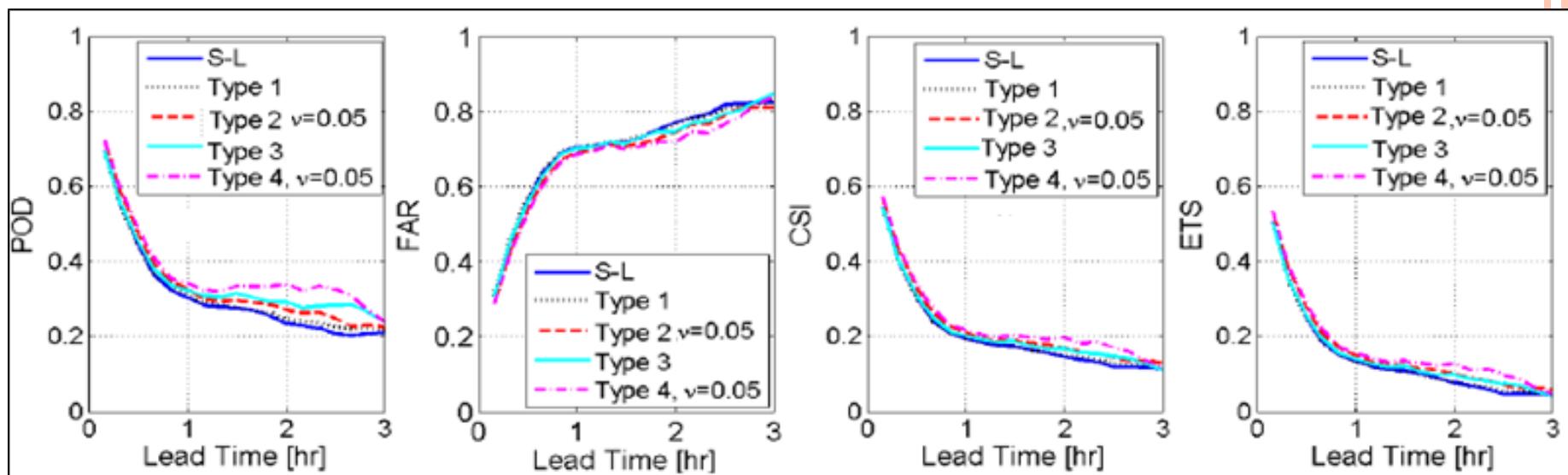
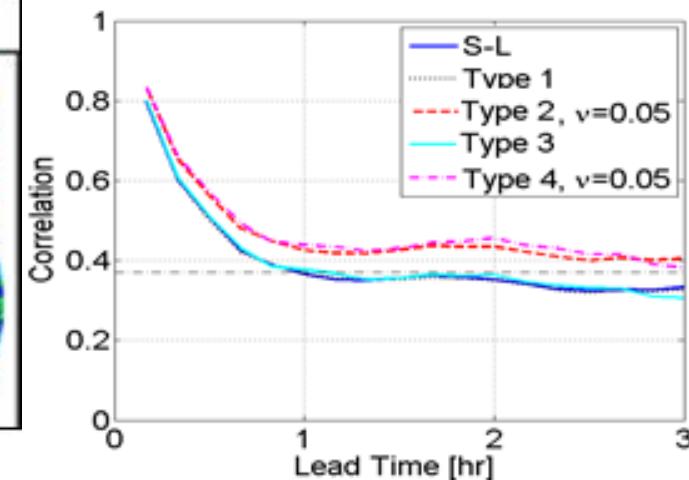
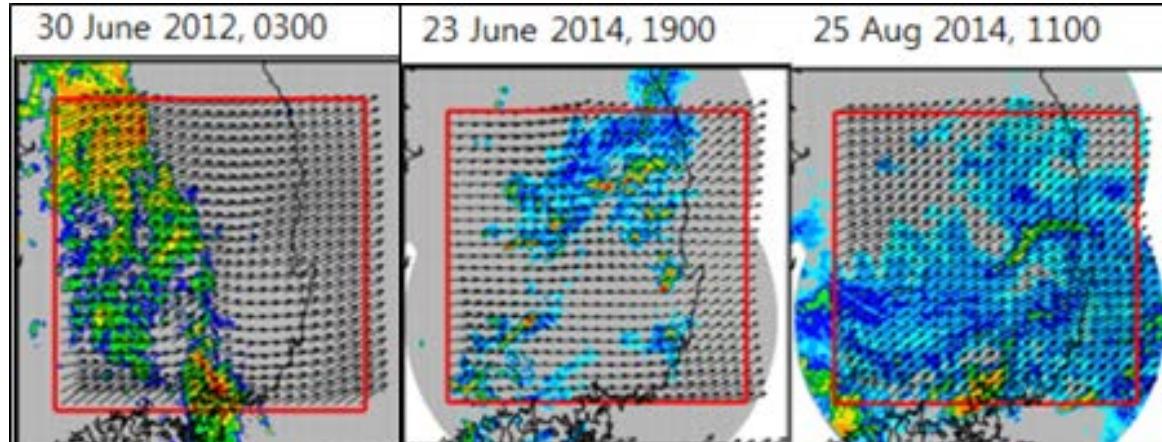
17 Sep 2012, 1200



Type 3, 4 (inclusion of Burgers' equation) outperform

# NON-STATIONARY MOTION VECTORS

$$\text{Var}(\|\nabla \cdot \mathbf{u}\|) \leq 0.13$$



Type 2, 4 (inclusion of diffusion equation) perform better

# SUMMARY

- Introduced nowcasting based on advection (diffusion) equation with Burgers' equation
- Performance:  
MAPLE ~ Advection eq. < Advection eq. + Burgers eq.  
(S-L ~ Type1 < Type2 < Type 3 < Type 4)
- Use of diffusion term and non-stationary motion vector improves forecasting skill scores
- When nonstationarity of motion fields is strong, the precipitation forecasts using Burgers' equation (Type3, Type 4) show significant improvement.

