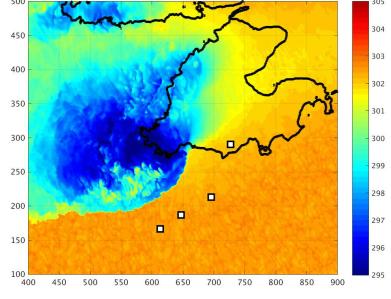
FROM ANALYTIC MODELS TO OSSES: USING SYNTHETIC OBSERVATIONS TO INFORM UAS CONFIGURATION FOR ATMOSPHERIC

Sensing



OU UAS Workshop 29 Oct. 2019 Adam Houston University of Nebraska – Lincoln



George Limpert – University of Nebraska-Lincoln Jason Keeler – Central Michigan University National Science Foundation grants OIA-1539070 and IIS-1527113

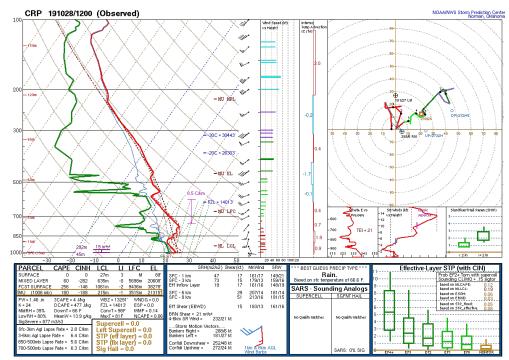






Determine the configuration and CONOPS of an observing platform to maximize its value in the forecasting process

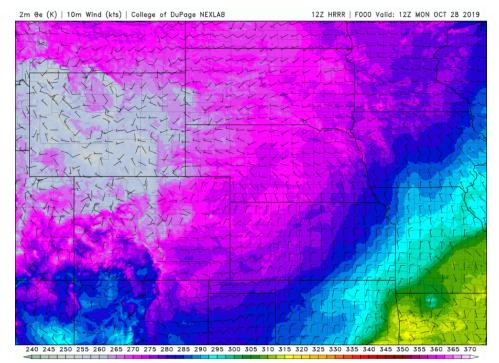
Heuristics for manual forecasting





Determine the configuration and CONOPS of an observing platform to maximize its value in the forecasting process

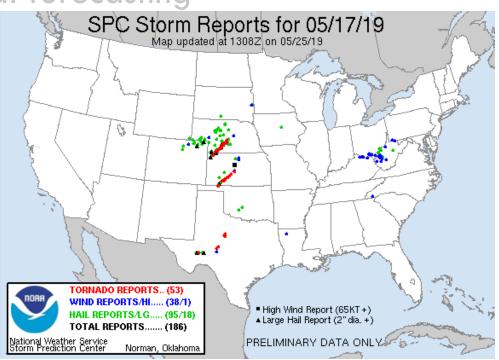
- Heuristics for manual forecasting
- NWP guidance





Determine the configuration and CONOPS of an observing platform to maximize its value in the forecasting process

- Heuristics for manual forecasting
- NWP guidance
- Verification





The value of new observations can be assessed through answers to the following:

- Are the data collected at the **right time**?
- Are the data collected in the right place?
- Are the data collected by the right instrument?

...and how right?



Ideally we would collect data at multiple times, multiple places, and with multiple instruments and see which combination produces the largest impact on one or more of the three components.





Synthetic data

"Simulated" data, "collected" across the parameter space defined by time, place, and instrument configuration

Process \rightarrow Synthetic data are inserted into a component of the forecast process and the impact is assessed.





- 1. Analytic models
- 2. Large eddy simulations (LES)
- 3. Ensemble sensitivity analysis (ESA)
- 4. Observing system simulations experiments (OSSE)



Atmospheric data are prescribed using an analytic function

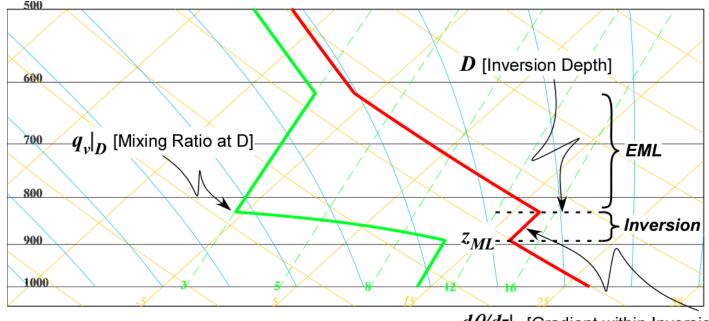
Simulated instrument is "operated" within this idealized environment

- Pros
 - Extensive parameter space can be explored

Right time?
Right place?
Right instrument?

- Cons
 - It's analytic and therefore highly simplified
 - Not good for evaluating NWP skill

"Sounding Characteristics that Yield Significant Convective Inhibition Errors Due to Ascent Rate and Sensor Response of In-Situ Profiling Systems" (Houston and Keeler 2019)



 $d\theta/dz|_{I}$ [Gradient within Inversion]

Lincoln

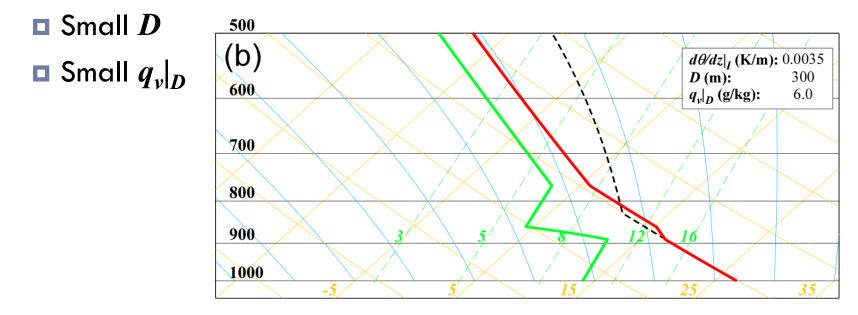
5059 analytic soundings

The sounding characteristics that result in the largest relative CIN errors are also the characteristics that result in the smallest CIN

JNIVERSITY **1** OF

Incoln

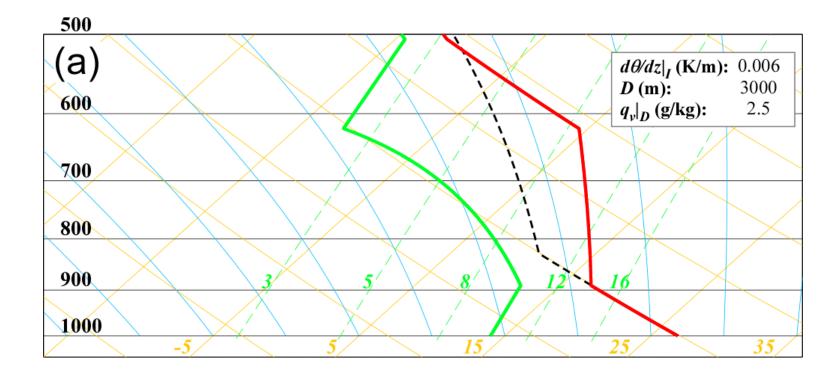
• Small $d\theta/dz|_I$



Sounding characteristics that contribute to large CIN do not proportionally increase the CIN error

UNIVERSITY **1** OF

Lincoln





Atmospheric data come from large eddy simulations

Simulated instrument is "operated" within this idealized environment

Pros

- Large parameter space can be explored
- Addresses all assessment components



- Cons
 - Parameter space won't be nearly as large as with analytic approach because some of the parameter space would require multiple LES
 - Not good for evaluating NWP skill



"The Impact of Sensor Response and Airspeed on the Representation of the Convective Boundary Layer and Airmass Boundaries by Small Unmanned Aircraft Systems" (Houston and Keeler 2019, JAOT)

Determine UAS system capabilities required to accurately represent thermodynamic properties of,

- The CBL
- Airmass boundaries

Specific focus on sensor response and aircraft speed

LES: Example



CBL simulations:

- Domain: 24 km x 24 km x 5 km
- Insolution: Mid-day, April 15, 40°N
- Rotary-wing aircraft

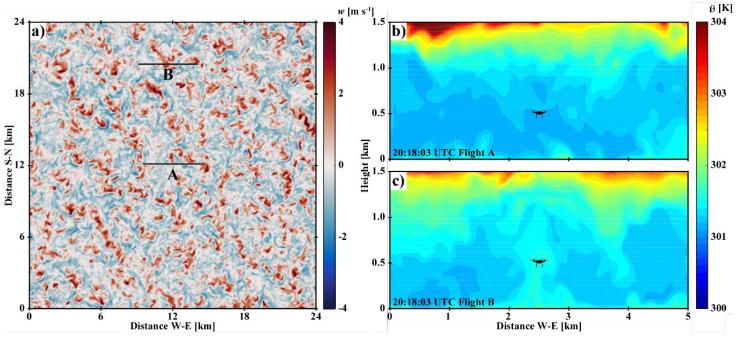
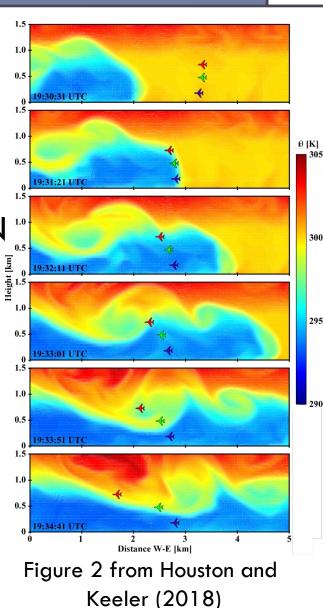


Figure 1 from Houston and Keeler (2018)

LES: Example

Airmass boundary simulations:

- Domain: 244 km x 5 km (2D x-z)
- Insolation: Mid-day, April 15, 40°N
- Initial cold block: -15 K
- Fixed-wing aircraft

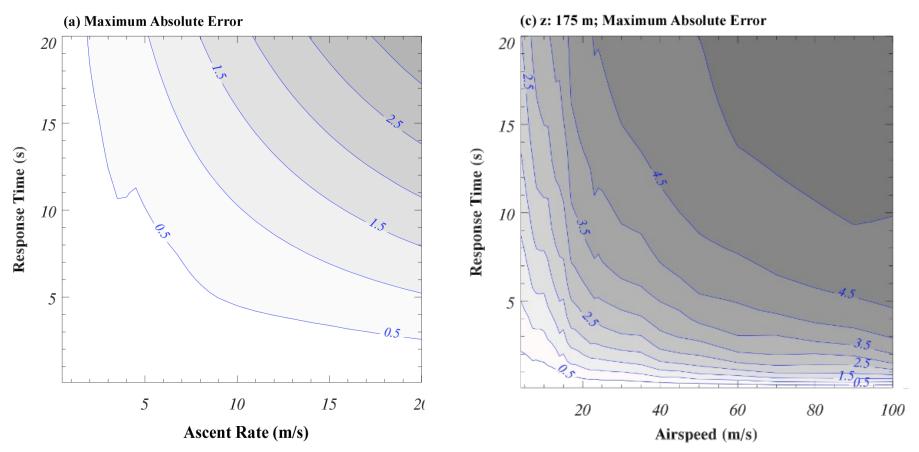




LES: Example

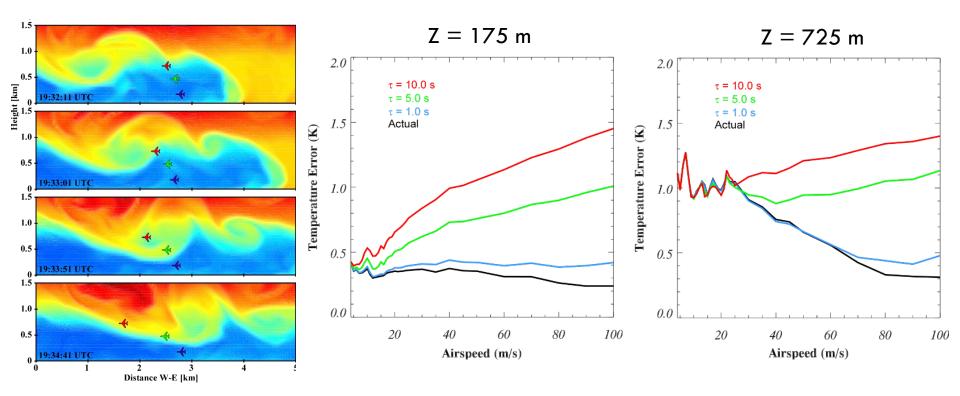


For both the CBL and airmass boundary experiments, absolute errors scale directly with sensor response time and flight speed.



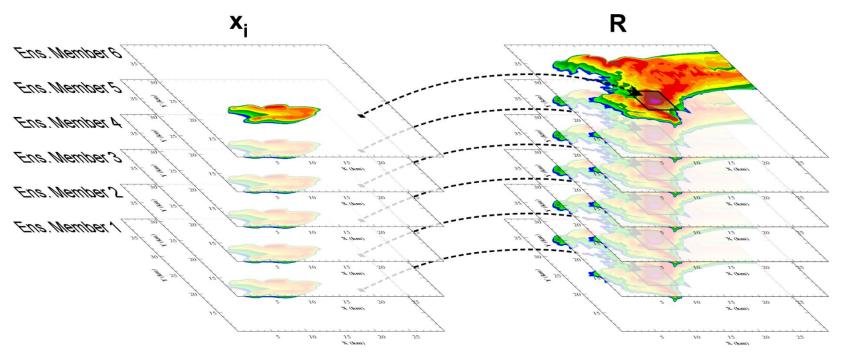


Errors relative to a representative snapshot for the airmass boundary simulation: If aircraft encounter the rapidlyevolving wake, the accuracy in representing a snapshot state of the atmosphere degrades with decreasing airspeed.





Ensemble sensitivity analysis: Estimate the sensitivity of a dynamical model to observations by statistically relating perturbations to the forecast response (Ancell and Hakim 2007)







- Atmospheric data come numerical simulations
- No instruments are actually "operated"
 - Pros
 - Sensitivity can be evaluated over a large area and numerous lead times
 - Cons
 - Doesn't actually use synthetic data so observations aren't simulated

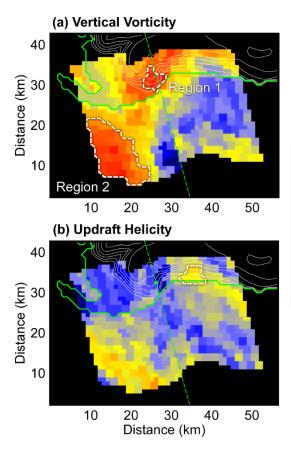
Right time?
Right place?
Right instrument?

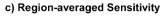


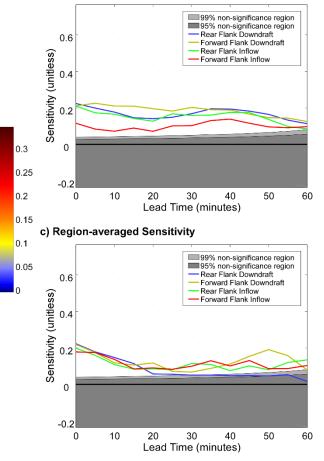
"Ensemble Sensitivity Analysis for Targeted Observations of Supercell Thunderstorms" (Limpert and Houston 2018, MWR)

Supercell simulation with 101 ensemble members

Sensitivity assessed via multivariate regression



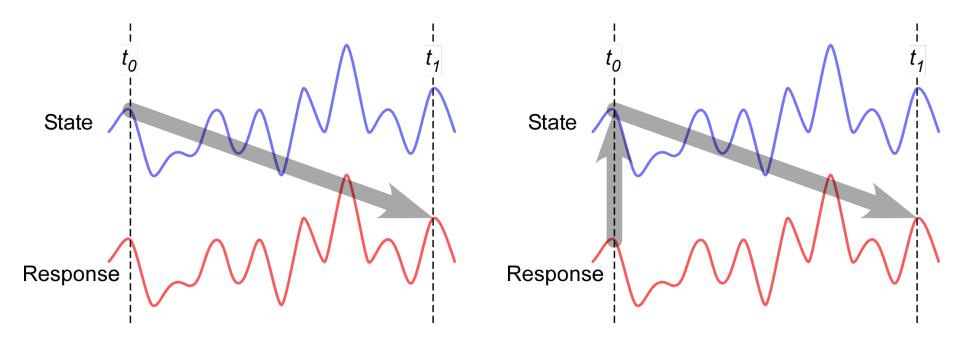






Challenges of storm-scale ESA:

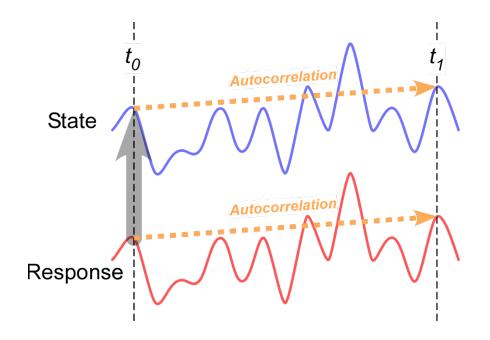
- Linearity is a poor assumption
- Auto-correlation mimics sensitivity





Challenges of storm-scale ESA:

- Linearity is a poor assumption
- Auto-correlation mimics sensitivity





Atmospheric data come from LES (nature run)

Simulated instrument is "operated" within this idealized environment

Synthetic data are assimilated into a NWP model to quantify impact

Pros

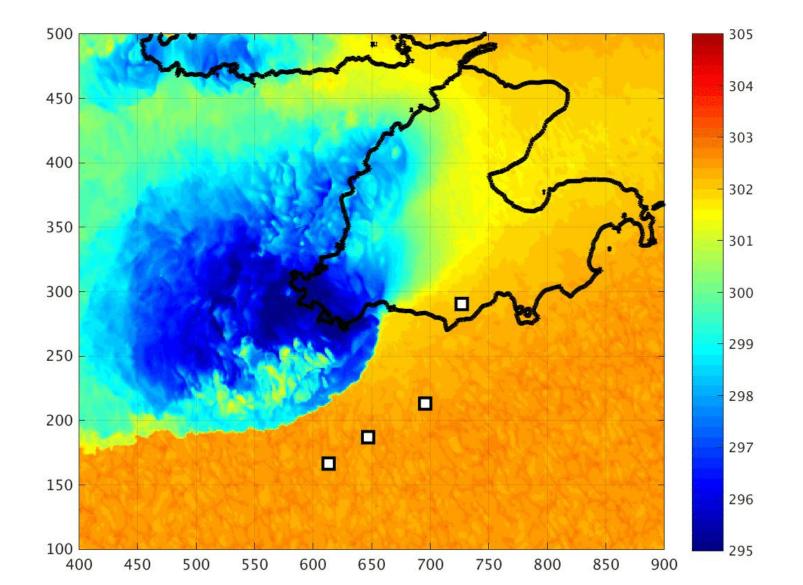
- Can evaluate NWP skill
- Addresses all assessment components

Right time?
Right place?
Right instrument?

- Cons
 - Parameter space is limited but can be narrowed with the prior techniques
 - Far more complicated than previous methods

OSSE: Example





Summary



There isn't a single "golden" technique for determining the configuration and CONOPS of an observing platform that maximizes its value in the forecasting process

- 1. Analytic models
- 2. Large eddy simulations (LES)
- 3. Ensemble sensitivity analysis (ESA)
- 4. Observing system simulations experiments (OSSE)