Stanford | ENGINEERING
Mechanical Engineering

SAND2015-1709PE

*Exceptional service in the national interest*

Sandia National Laboratories

# Improving RANS Modeling of Trailing Edge Slot Film Cooling Flows

and

# Using Machine Learning to Detect When RANS will Fail

NSF Graduate Research Fellowship Program

GE Aviation

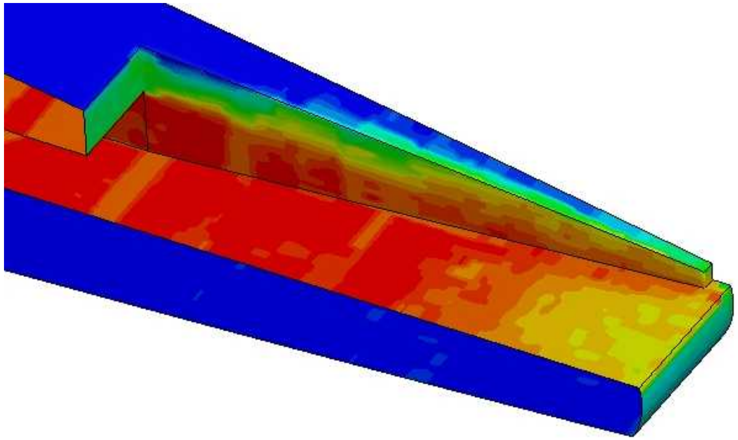
Sandia National Laboratories

U.S. DEPARTMENT OF ENERGY

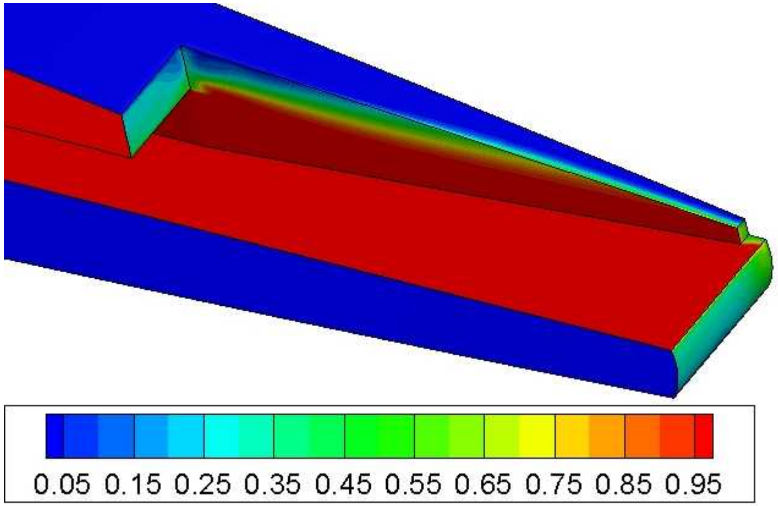
NNSA National Nuclear Security Administration

# Motivation

Experiment:



RANS:

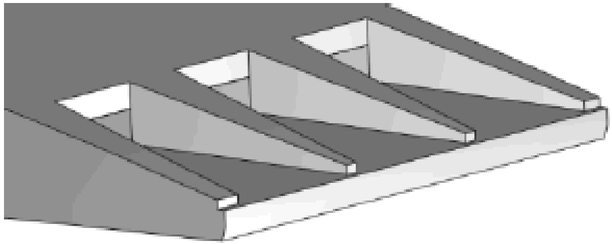


# Objectives

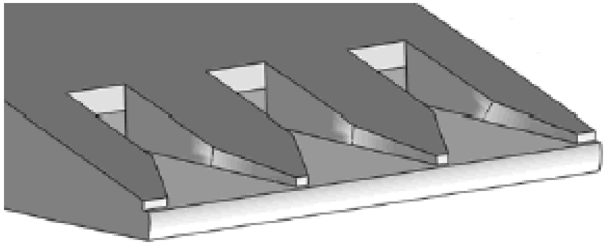
- Conduct experiments to increase understanding of trailing edge slot film cooling flow fields and coolant concentration distributions
- Use these experiments as a database to drive model improvements for these flows

# Experimental Database

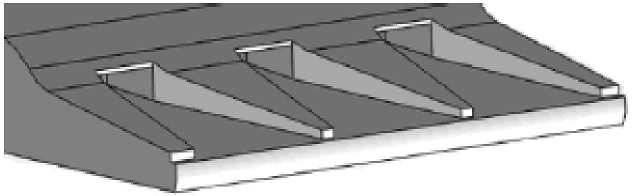
- 15 cases, 9 geometries
    - Encompass datasets obtained by J. Ling and M. Benson
    - 3D velocity and concentration data
    - Varying geometry, blowing ratio, and Reynolds number



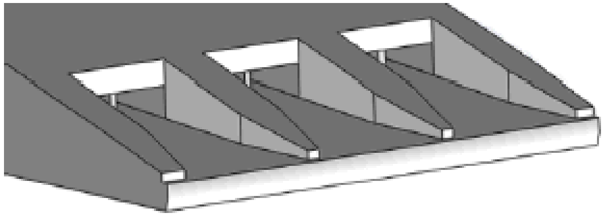
(a) Baseline



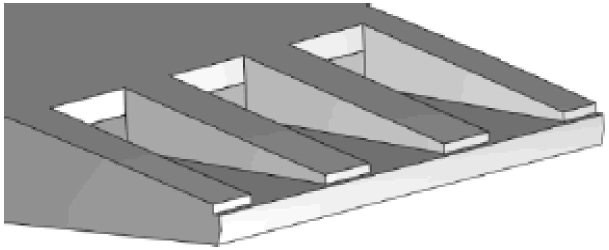
(b) Shield



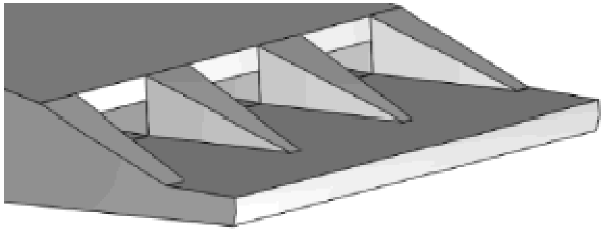
(c) Dolphin



(d) Island



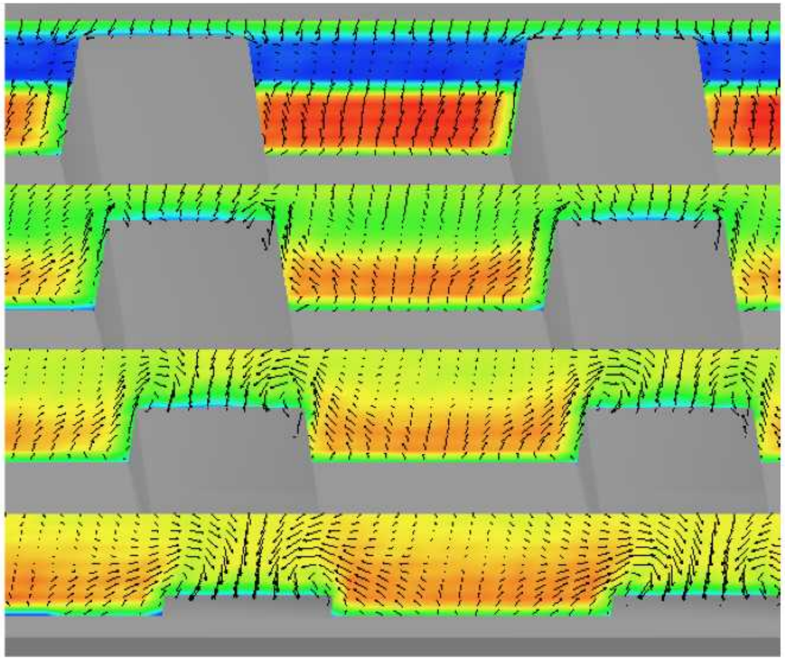
(e) Straight Lands



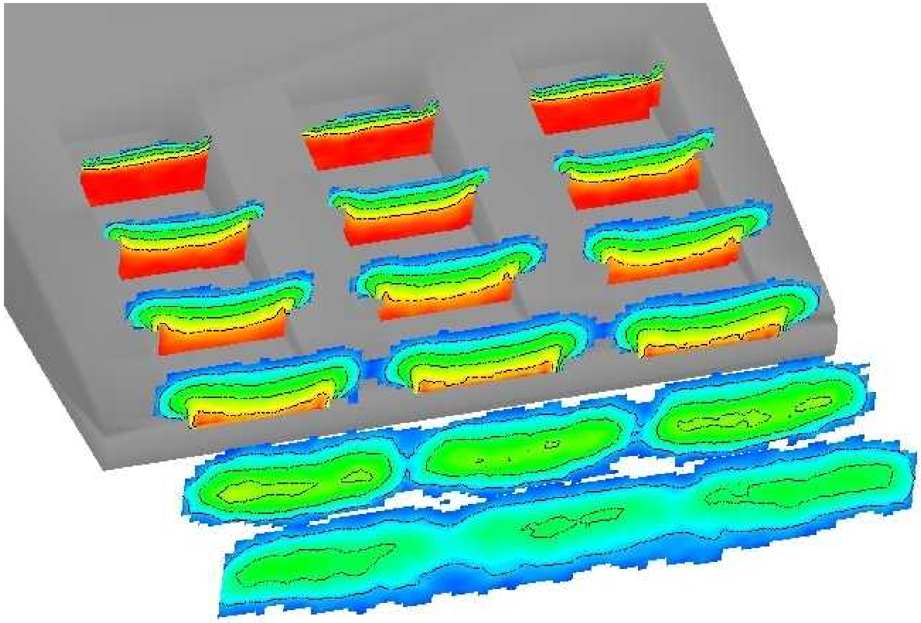
(f) Strongly Tapered Lands

# Experimental Results: MRV and MRC

Streamwise velocity contours overlaid with in-plane velocity vectors



Contours of coolant concentration



- ➢ New type of data—millions of points in a 3D Cartesian grid
- ➢ How can this data be leveraged to improve RANS models?

# Turbulent Scalar Flux Models

Advection Diffusion equation:

$$\frac{dc}{dt} + \nabla \cdot \mathbf{u}c = \alpha \nabla^2 c$$

Reynolds Averaged Advection Diffusion (RAAD) equation:

$$\nabla \cdot \bar{\mathbf{u}}\bar{c} = \alpha \nabla^2 \bar{c} - \nabla \cdot \boxed{\overline{\mathbf{u}'c'}}$$

Gradient diffusion hypothesis:

$$\overline{\mathbf{u}'c'} = -\alpha_t \nabla \bar{c}$$

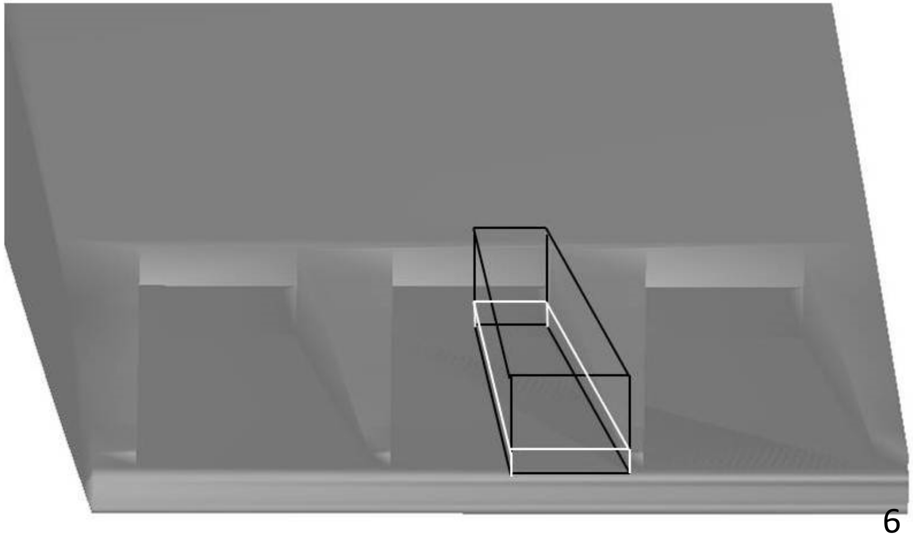
Reynolds analogy:

$$\alpha_t = \frac{\nu_t}{\boxed{Sc_t}}$$

# Optimal Turbulent Schmidt Number

- Default Value: $Sc_t = 0.85$ based on flat plate boundary layer
- What is best value for trailing edge slot film cooling?
- How to evaluate?
  - *Don't* want to just compare selected profiles—want a smarter way to use our data
  - Compare 3D experimental data + CFD results
  - Use a quantitative error metric
  - Optimize $Sc_t$ for all 15 cases in experimental database

$$\boxed{E = \frac{1}{n} \sum_{ROI} \left| c_{RANS} - c_{MRC} \right|}$$



# Optimal Turbulent Schmidt Number

- No single $Sc_t$ value optimal in all cases

| Case # | Case Description | Large ROI | Near Wall ROI |
|---|---|---|---|
| 1 | Generic, $BR = 1.5$, $Re = 250000$ | 0.65 | 0.45 |
| 2 | Generic, $BR = 1.5$, $Re = 136000$ | 1.05 | 0.45 |
| 3 | Generic, $BR = 1.3$, $Re = 136000$ | 1.05 | 0.45 |
| 4 | Generic, $BR = 1.0$, $Re = 136000$ | 1.05 | 0.65 |
| 5 | Generic Pin Fin, $BR = 1.3$, $Re = 110000$ | 0.85 | 0.45 |
| 6 | Baseline, $BR = 1.3$, $Re = 110000$ | 0.45 | 0.25 |
| 7 | Baseline, $BR = 1.0$, $Re = 110000$ | 0.65 | 0.45 |
| 8 | Baseline, $BR = 0.7$, $Re = 110000$ | 0.85 | 0.45 |
| 9 | Shield, $BR = 1.3$, $Re = 110000$ | 0.85 | 0.45 |
| 10 | Shield, $BR = 1.0$, $Re = 110000$ | 0.65 | 0.45 |
| 11 | Bump Shield, $BR = 1.3$, $Re = 110000$ | 0.65 | 0.45 |
| 12 | Dolphin, $BR = 1.3$, $Re = 110000$ | 0.85 | 0.45 |
| 13 | Island, $BR = 1.3$, $Re = 110000$ | 0.65 | 0.45 |
| 14 | Straight Lands, $BR = 1.3$, $Re = 110000$ | 0.65 | 0.45 |
| 15 | Strongly Tapered Lands, $BR = 1.3$, $Re = 110000$ | 0.65 | 0.45 |

# Optimal Turbulent Schmidt Number

- 0.45 is optimal value in ROI-2 in 13 out of 15 cases
  - Recommend using $Sc_t = 0.45$ for more accurate adiabatic effectiveness predictions using RKE

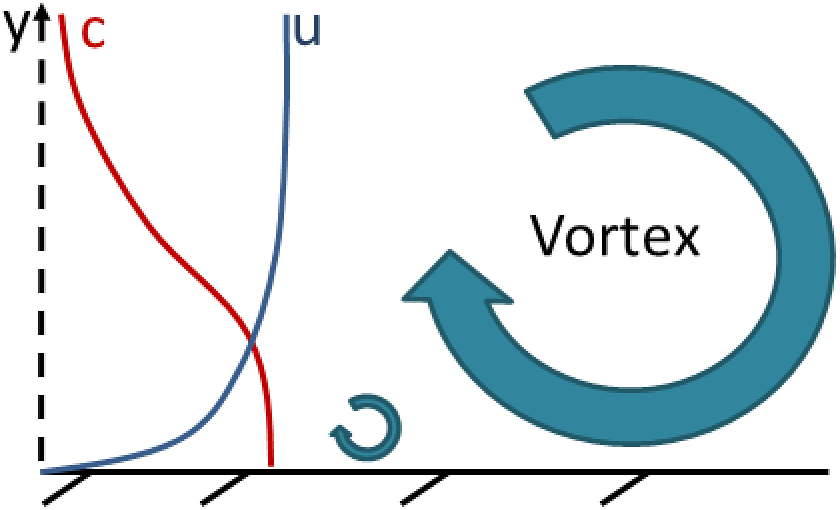
| Case # | Case Description | Large ROI | Near Wall ROI |
|---|---|---|---|
| 1 | Generic, $BR = 1.5$, $Re = 250000$ | 0.65 | 0.45 |
| 2 | Generic, $BR = 1.5$, $Re = 136000$ | 1.05 | 0.45 |
| 3 | Generic, $BR = 1.3$, $Re = 136000$ | 1.05 | 0.45 |
| 4 | Generic, $BR = 1.0$, $Re = 136000$ | 1.05 | 0.65 |
| 5 | Generic Pin Fin, $BR = 1.3$, $Re = 110000$ | 0.85 | 0.45 |
| 6 | Baseline, $BR = 1.3$, $Re = 110000$ | 0.45 | 0.25 |
| 7 | Baseline, $BR = 1.0$, $Re = 110000$ | 0.65 | 0.45 |
| 8 | Baseline, $BR = 0.7$, $Re = 110000$ | 0.85 | 0.45 |
| 9 | Shield, $BR = 1.3$, $Re = 110000$ | 0.85 | 0.45 |
| 10 | Shield, $BR = 1.0$, $Re = 110000$ | 0.65 | 0.45 |
| 11 | Bump Shield, $BR = 1.3$, $Re = 110000$ | 0.65 | 0.45 |
| 12 | Dolphin, $BR = 1.3$, $Re = 110000$ | 0.85 | 0.45 |
| 13 | Island, $BR = 1.3$, $Re = 110000$ | 0.65 | 0.45 |
| 14 | Straight Lands, $BR = 1.3$, $Re = 110000$ | 0.65 | 0.45 |
| 15 | Strongly Tapered Lands, $BR = 1.3$, $Re = 110000$ | 0.65 | 0.45 |

# Optimal Turbulent Schmidt Number

- In all cases, optimal $Sc_t$ in near surface ROI is less than in larger ROI
  - Need improved near wall turbulent mixing modeling

| Case # | Case Description | Large ROI | Near Wall ROI |
|---|---|---|---|
| 1 | Generic, $BR = 1.5$, $Re = 250000$ | 0.65 > | 0.45 |
| 2 | Generic, $BR = 1.5$, $Re = 136000$ | 1.05 > | 0.45 |
| 3 | Generic, $BR = 1.3$, $Re = 136000$ | 1.05 > | 0.45 |
| 4 | Generic, $BR = 1.0$, $Re = 136000$ | 1.05 > | 0.65 |
| 5 | Generic Pin Fin, $BR = 1.3$, $Re = 110000$ | 0.85 > | 0.45 |
| 6 | Baseline, $BR = 1.3$, $Re = 110000$ | 0.45 > | 0.25 |
| 7 | Baseline, $BR = 1.0$, $Re = 110000$ | 0.65 > | 0.45 |
| 8 | Baseline, $BR = 0.7$, $Re = 110000$ | 0.85 > | 0.45 |
| 9 | Shield, $BR = 1.3$, $Re = 110000$ | 0.85 > | 0.45 |
| 10 | Shield, $BR = 1.0$, $Re = 110000$ | 0.65 > | 0.45 |
| 11 | Bump Shield, $BR = 1.3$, $Re = 110000$ | 0.65 > | 0.45 |
| 12 | Dolphin, $BR = 1.3$, $Re = 110000$ | 0.85 > | 0.45 |
| 13 | Island, $BR = 1.3$, $Re = 110000$ | 0.65 > | 0.45 |
| 14 | Straight Lands, $BR = 1.3$, $Re = 110000$ | 0.65 > | 0.45 |
| 15 | Strongly Tapered Lands, $BR = 1.3$, $Re = 110000$ | 0.65 > | 0.45 |

# Near Wall Correction



- Scalar transport near wall fundamentally different from momentum transport

$$\overline{u'v'} \propto y^3$$

$$\overline{v'c'} \propto y^2$$

- Causes a breakdown in the Reynolds analogy

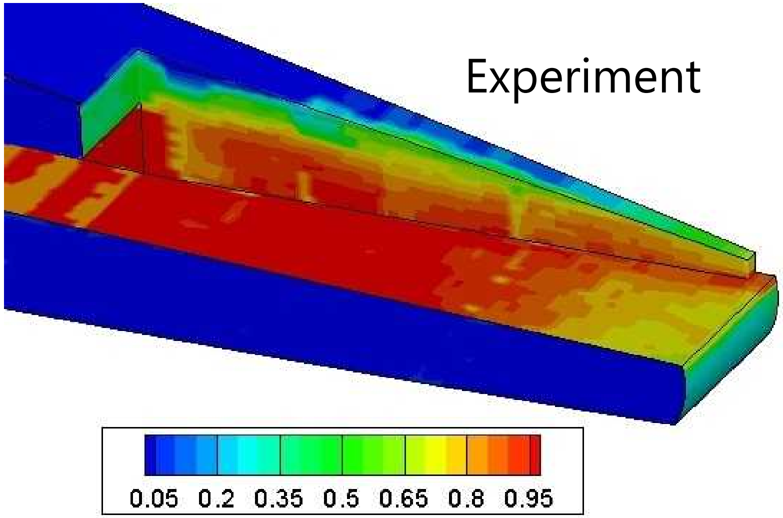
$$l = y(1 - e^{-y^+/A})$$

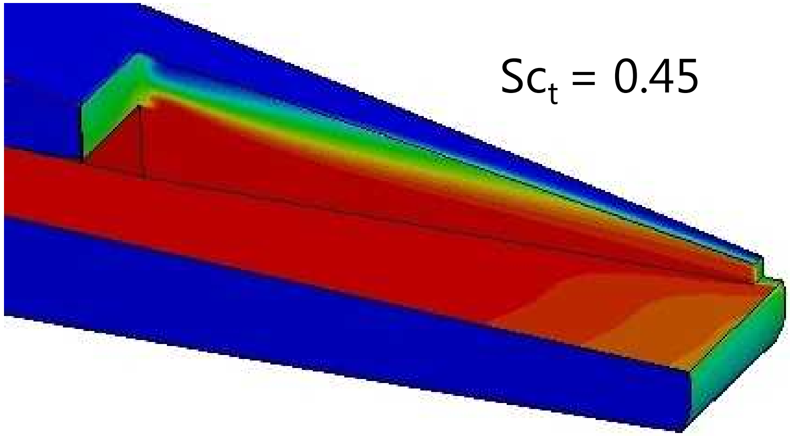
Proposed Correction:

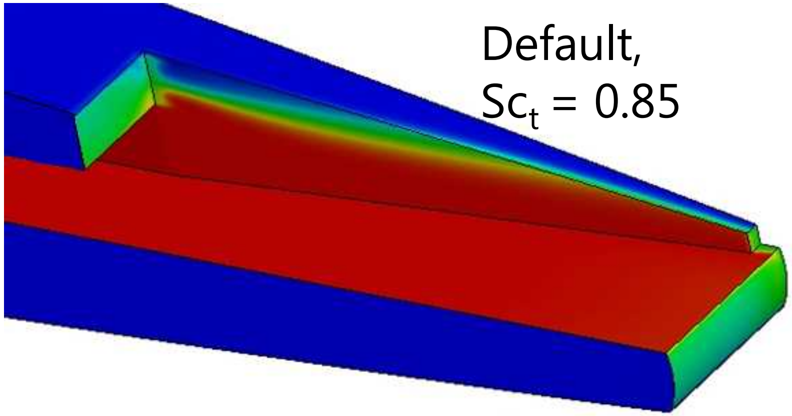
$$\boxed{\alpha_{t,corr} = \frac{\nu_t}{Sc_t(1 - e^{-Re_t/70})}}$$

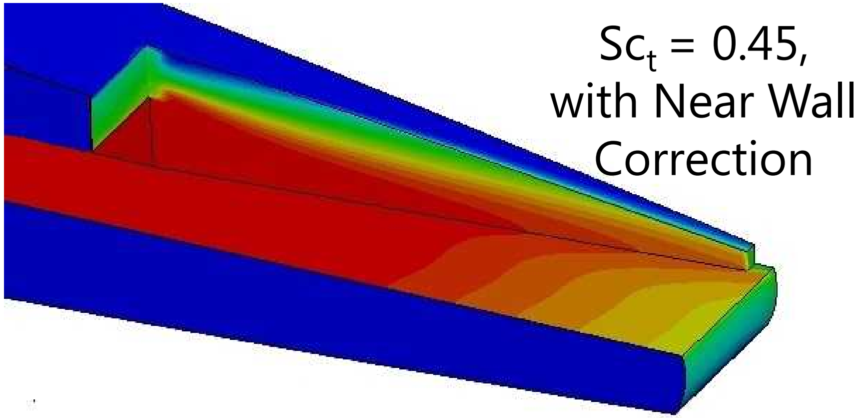
$$Re_t = \frac{\sqrt{k} * (Wall\ \ Distance)}{\nu}$$

# Near Wall Correction: Adiabatic Effectiveness

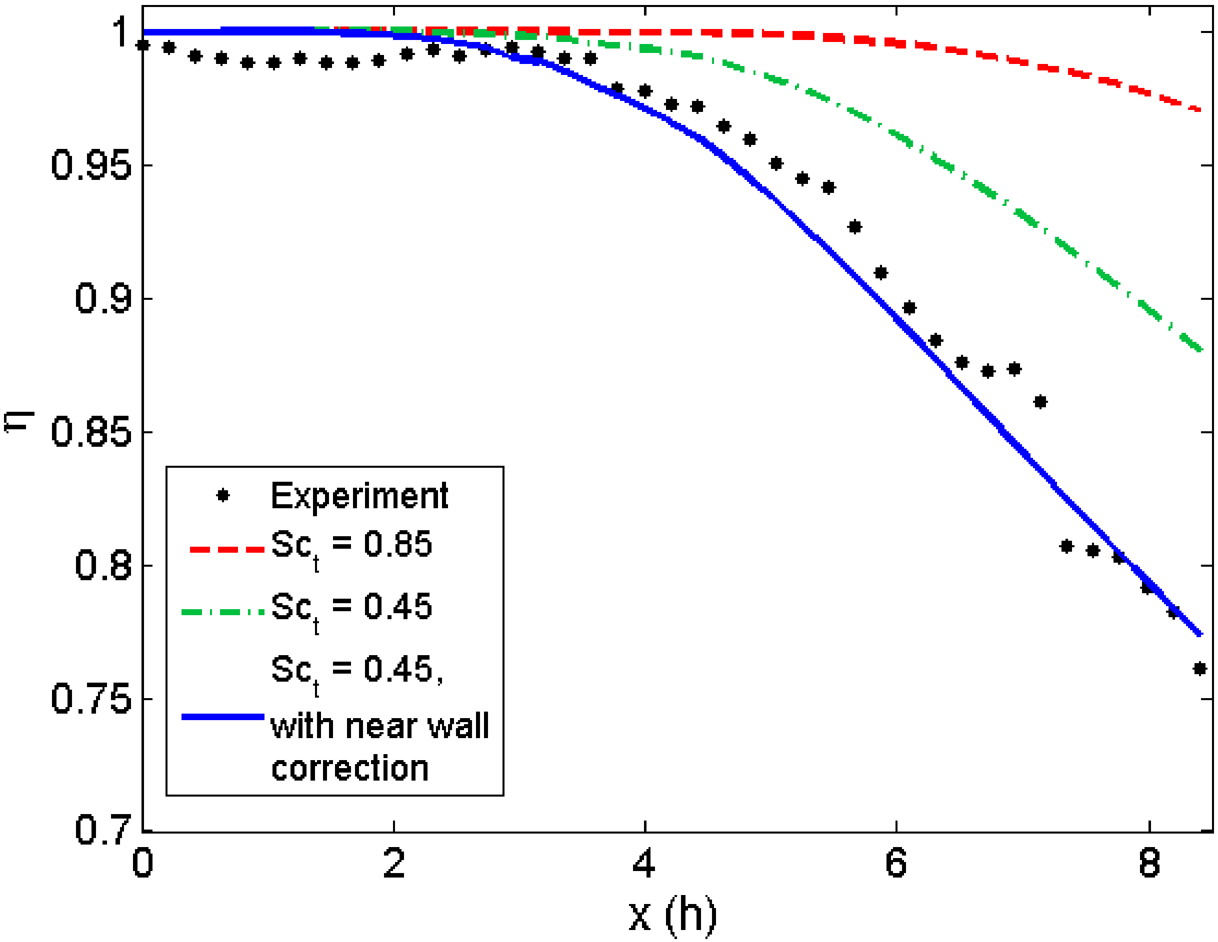

Experiment


$Sc_t = 0.45$

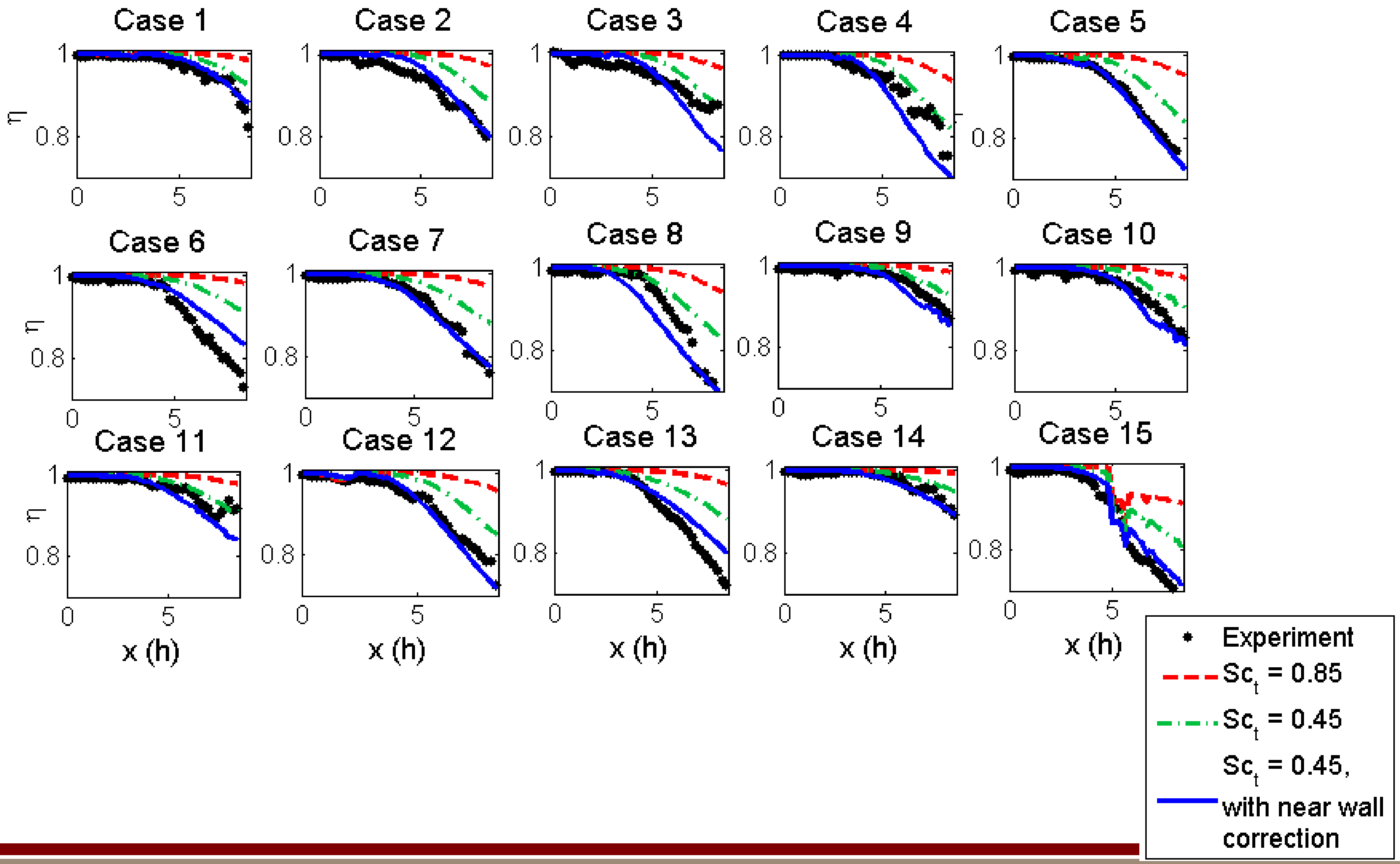

Default,
$Sc_t = 0.85$


$Sc_t = 0.45$,
with Near Wall
Correction

# Near Wall Correction:
# Spanwise Averaged Adiabatic Effectiveness



# Near Wall Correction: Generalization



# Conclusions

- Used detailed, 3D, quantitative comparisons between experimental and CFD results to develop and validate a new near wall model

- Showed significant and robust predictive improvement

# USING MACHINE LEARNING TO DETECT REGIONS OF HIGH RANS UNCERTAINTY

# Motivation and Objective

- Current CFD simulations often generate gigabytes to terabytes (or more) of data
- How can we leverage this data to improve our turbulence models?
- Key application: RANS models are right sometimes, wrong sometimes—how can we tell the difference?
    - Current method: Expert opinion or validation experiments
    - My research: Use machine learning algorithms to detect regions of high RANS uncertainty

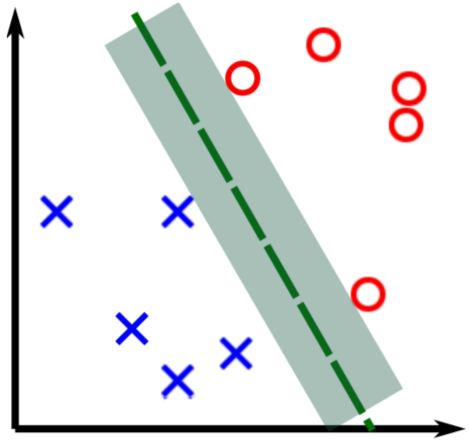
# Machine Learning

- Set of data-driven algorithms for regression, classification, clustering
- Examples: linear regression, neural nets, support vector machines
- Has been broadly applied in finance, software engineering, retail
- More of a “black box” mentality—not physics-driven

$x$

Machine learning algorithm

$y$



# The Basic Idea

- Use machine learning to detect when basic RANS assumptions are violated
- Train the algorithms using a database of high fidelity simulations for different flow configurations
    - Input: Local flow variables from RANS
    - Output: Binary flag– “on” if RANS assumption breaks down, “off” if assumption fine
- Applications:
    - Can quickly post-process RANS simulation to determine whether it’s reliable in region of interest
    - Determine what corrections could improve predictions in critical regions
    - Enable adaptive corrections in simulation

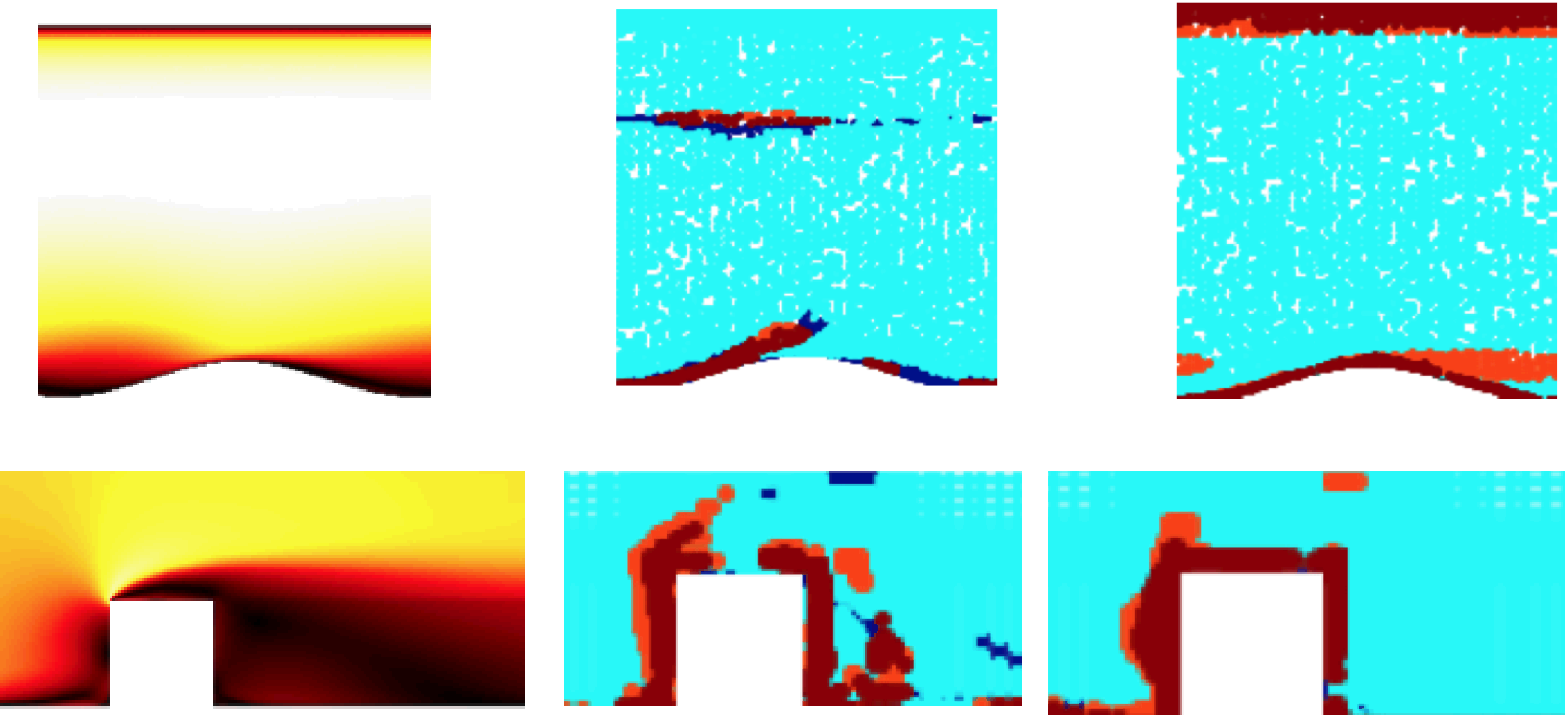
# Sample Results:

● True Negative
● False Negative
● True Positive
● False Positive

Contours of Velocity Magnitude

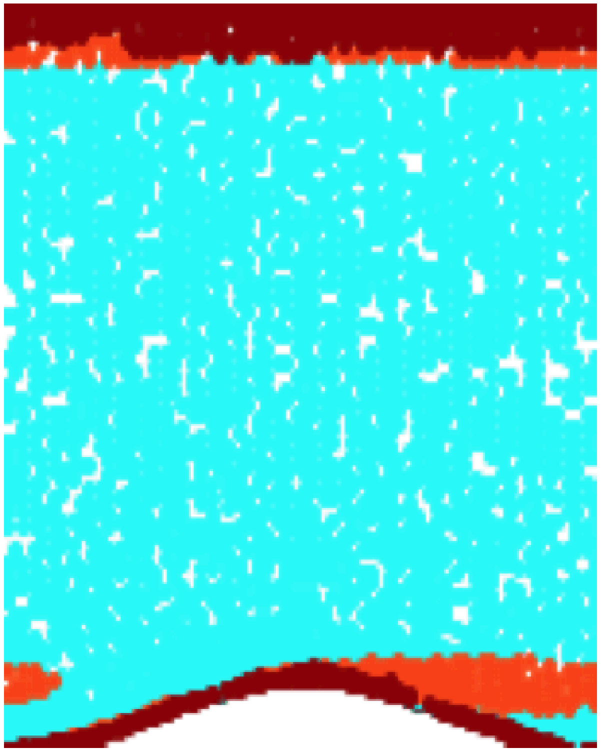
Negative Turbulent Viscosity

Anisotropy

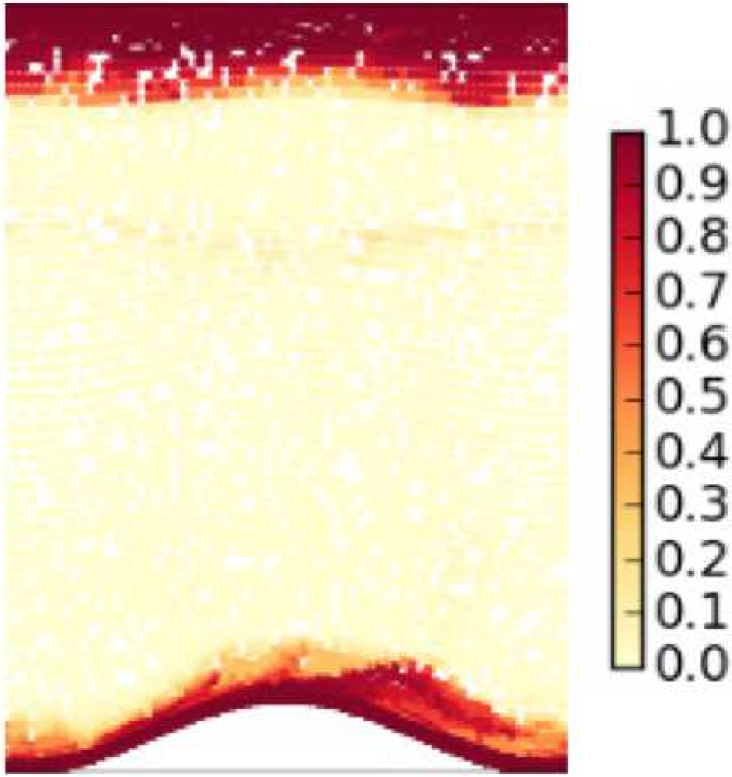


# Sample Results: Marker Confidence

Marker Predictions



Marker Confidence



# Summary

- RANS would be a lot more useful if we knew when to believe it
- Machine learning can provide the solution
- Big Picture: Machine learning has the potential to have a huge impact in fluid mechanics and heat transfer
    - Better switching functions in hybrid models?
    - Better wall models?
    - Detecting failure modes?
    - Learning from compilations of simulation results?