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Turbulent Flow Simulations for Machine Learning

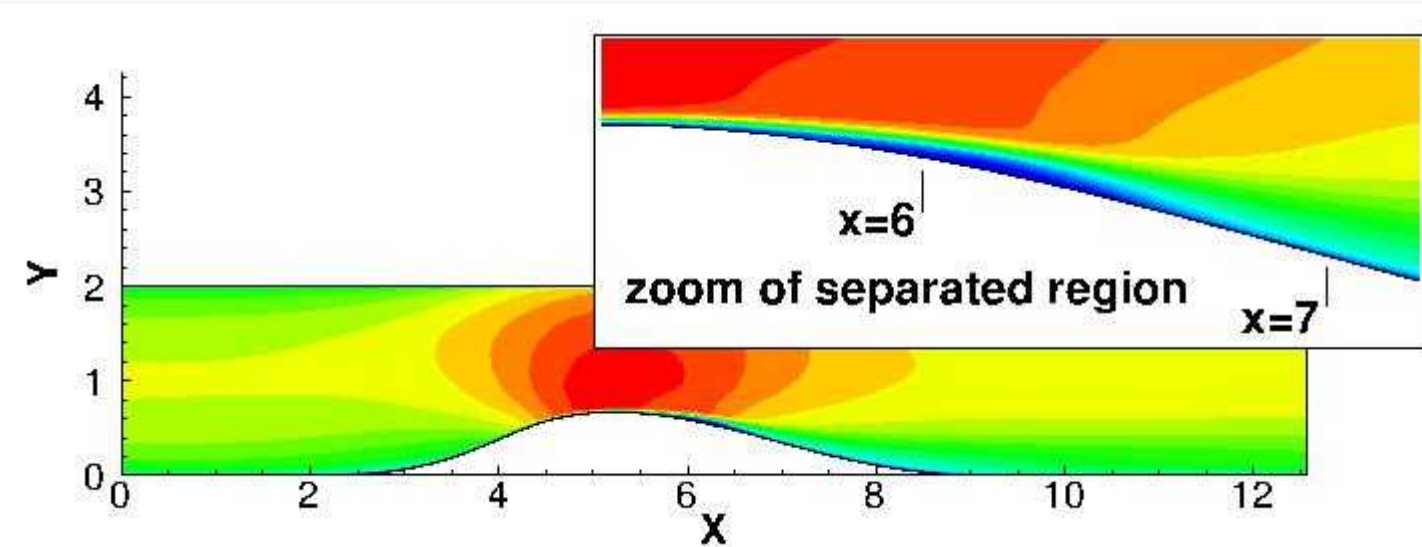
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Problem

Directly resolving turbulent flow is computationally expensive. Reynolds Averaged Navier-Stokes (RANS) simulations do not resolve turbulence exactly, but employ empirical approximations that are computationally efficient. These RANS approximations are often inaccurate and lead to uncertainty that must be quantified. Machine Learning (ML) techniques have been developed to detect regions of high uncertainty. The ML algorithms are trained across a database of high fidelity Direct Numerical Simulations (DNS) and RANS simulations. The current database includes seven canonical flows, such as jets in crossflow and flows around bluff bodies. The goal of this project was to add a new flow configuration to the database: a converging-diverging channel.

Converging Diverging Channel



Why a CD channel?

- Canonical Flow
- Separation Region not accurately captured with RANS
- Readily available DNS dataset²

Sierra Fuego Setup

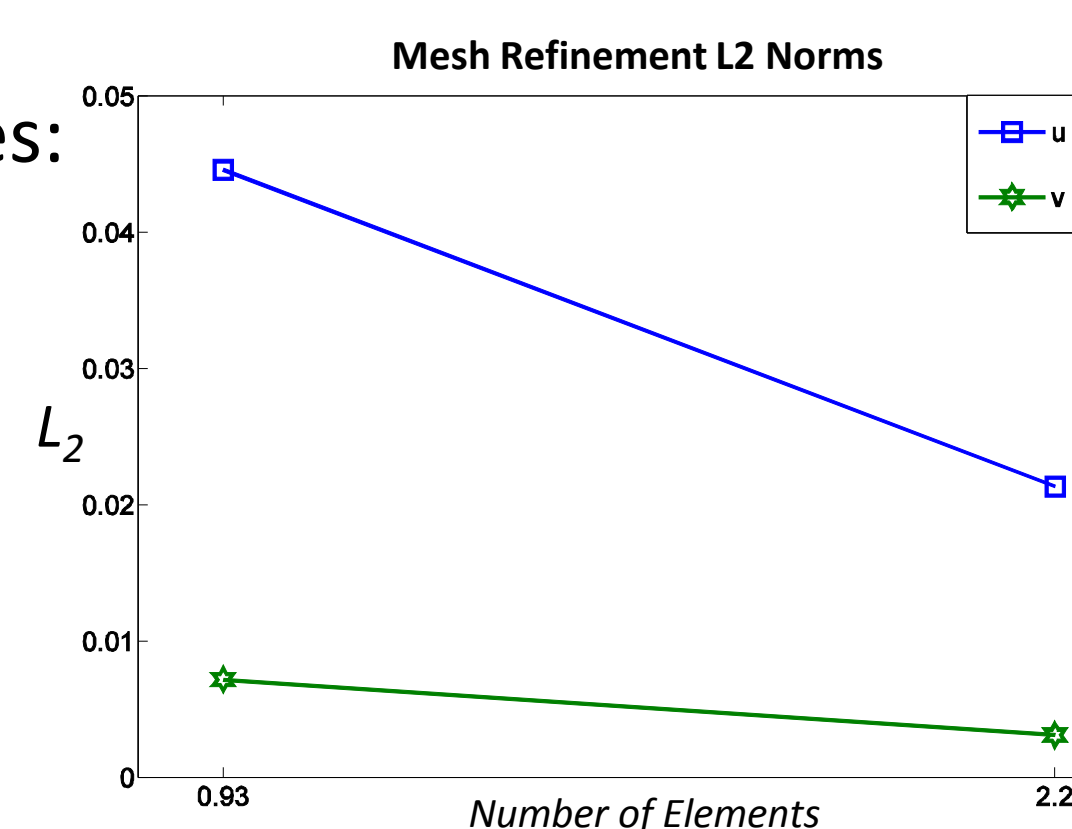
Sierra Fuego was used for the RANS. The simulation was set-up to reproduce the conditions used by Laval et al. in their DNS.

- Inlet – data from channel flow DNS¹
- Outlet – constant pressure outlet
- Top/Bottom walls – no slip walls, i.e. $u_i = 0$
- Reynolds Number of 12600 based on channel half-height, U_{max} , and kinematic viscosity

Mesh refinement across three meshes:

- 278k cells
- 930k cells
- 2.2M cells

An additional mesh of 4M elements is being run to complete the study.



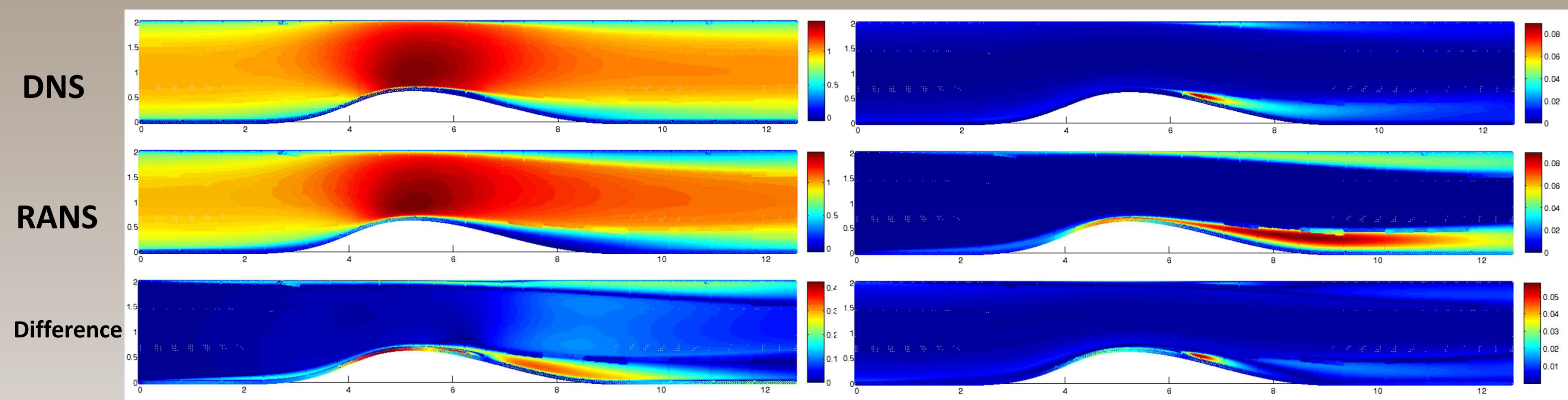
References

1. **Direct numerical simulation of turbulent channel flow up to $Re_{\tau}=590$** By: Moser, Robert D., John Kim, and Nagi N. Mansour. Phys. Fluids Physics of Fluids
2. **Direct Numerical Simulations of Converging-Diverging Channel Flow** By: Laval, Jean-Philippe, and Matthieu Marquillie. Progress in Wall Turbulence: Understanding and Modeling ERCOTAC Series
3. **Evaluation of Machine Learning Algorithms for Prediction of Regions of High RANS Uncertainty** By: Ling, Julia and Templeton, Jeremy. Physics of Fluids

Comparison to DNS

Streamwise Velocity

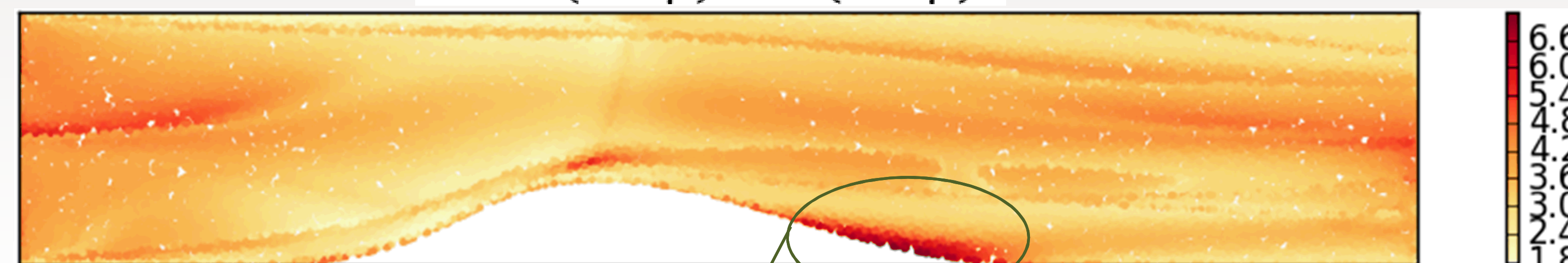
Turbulent Kinetic Energy



Contribution to Database

The Mahalanobis distance, D , indicates which regions of the flow are “new” to the database by quantifying the statistical distance between the points in the converging-diverging channel flow and the distribution of data points in the current database.

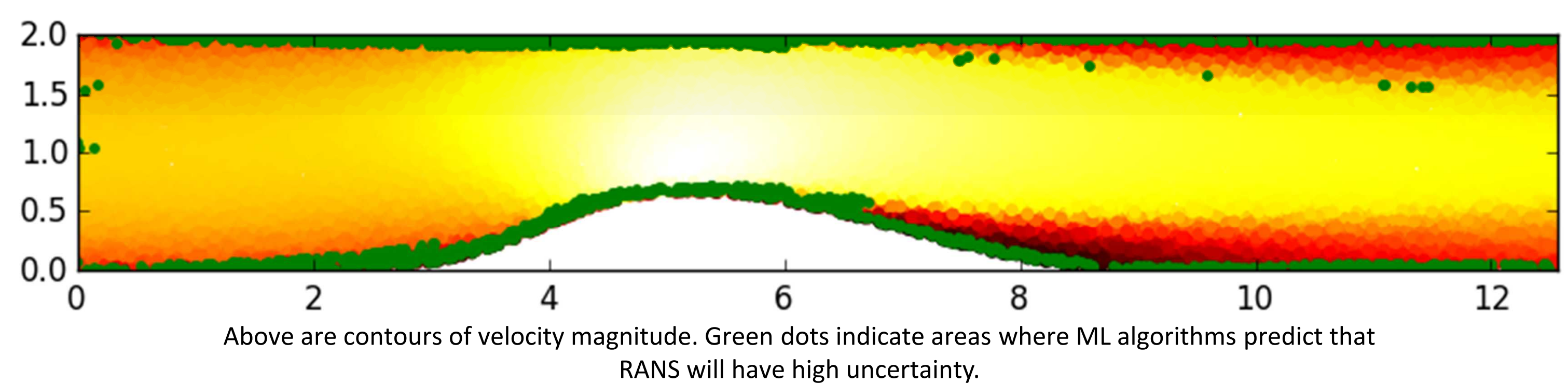
$$D = \sqrt{(x - \mu)^T \Sigma^{-1} (x - \mu)}$$



The separation and reattachment regions have high D indicating that they represent new flow regimes in the database.

Machine Learning Results

The converging-diverging channel flow was added to the ML database. The ML algorithms were used to predict in which regions of the flow the eddy viscosity model was violated.



The ML classifiers predict that the eddy viscosity assumption breaks down in the boundary layer, particularly immediately upstream and downstream of the bump. These results are in agreement with the fact that RANS error for mean velocity field was also greatest in the same regions. The ML classifier accuracy was 94% on this data set.

Conclusions

- Performed RANS simulation of converging-diverging channel using in house Sierra Fuego software
- Compared RANS results to DNS
- Added CD channel results to ML database of canonical flows
- Evaluated ML algorithm accuracy on the CD channel
- ML algorithm correctly identified regions of high RANS uncertainty