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Data-driven reduced order modelling of a bushfire analogy using variational autoencoders.

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A flow scenario involving turbulent fluid dynamics and nonlinear heat release has been simulated via direct numerical simulation (DNS) to serve as an analogy to bushfires, generating high-fidelity data for the development of an artifical intelligence (AI) prediction system. The complexity and high-dimensionality of these simulations present a significant challenge for traditional reduced-order modeling (ROM) techniques, often used to simplify and interpret such datasets. Recently, machine learning (ML) algorithms in the form of autoencoders (AE) and variational autoencoders (VAE) have shown promise as powerful alternatives to traditional ROM techniques [1]. The nonlinearity inherent to ML algorithms enables more compact and efficient representations of high-dimensional data often encountered in computational fluid dynamics (CFD). These dense latent space representations enable the temporal prediction of the evolution of complex flow fields, and the synthesis of data across the parameter space [2, 3].

In this work, a VAE is employed to uncover a latent space representation of turbulent flow fields of a bushfire analogy. Using this framework, this study demonstrated the ability to predict the time evolution of the flow fields and explore the parameter space of the heat release model, revealing insights into the underlying physics of this turbulent convective heat-driven flow.

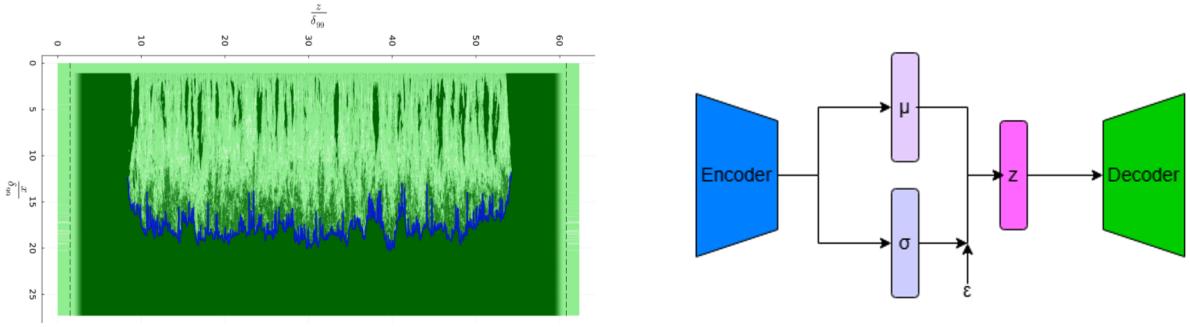

Figure 1: **(Left)** Fire front (blue) overlaid above the biomass as viewed from the top of the domain. Flow direction is from the top to the bottom. **(Right)** Flowchart of the VAE architecture.

References

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