5th ECMWF-ESA
Machine Learning
Workshop

Bologna, Italy | 13–17 April

Generative Adversarial Networks for Simulating Dynamic Interactions in Digital Twins of Coastal Ecosystems

Oscar Leung and Ye Ha Kim

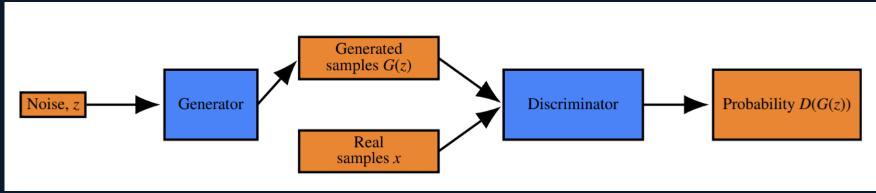
Reality gap in Coastal twins

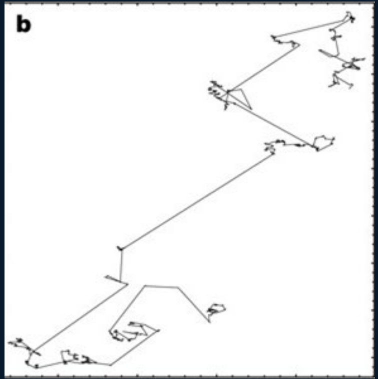
Coastal zones: High productivity vs. high anthropogenic stress.

Limitations of Deterministic Models: Computational cost & stochastic uncertainty.

The Goal: A "Generative Mirror" that looks, behaves, and connects.

GANs & Lévy Flights





GANs: Likelihood-free calibration of complex processes.

Lévy-flight Hypothesis: Capturing emergent biological foraging patterns.

Background Literature - Why Generative AI?

Data-Centric Engineering (2021), 2: e11
doi:10.1017/dce.2021.13

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RESEARCH ARTICLE

On generative models as the basis for digital twins

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Keywords: cGAN; digital twins; generative adversarial network; generative models; mirror models; stochastic finite elements

Abstract

A framework is proposed for generative models as a basis for *digital twins* or *mirrors* of structures. The proposal is based on the premise that deterministic models cannot account for the uncertainty present in most structural modeling applications. Two different types of generative models are considered here. The first is a physics-based model based on the stochastic finite element (SFE) method, which is widely used when modeling structures that have material and loading uncertainties imposed. Such models can be calibrated according to data from the structure and would be expected to outperform any other model if the modeling accurately captures the true underlying physics of the structure. The potential use of SFE models as digital mirrors is illustrated via application to a linear structure with stochastic material properties. For situations where the physical formulation of such models does not suffice, a data-driven framework is proposed, using machine learning and conditional generative adversarial networks (cGANs). The latter algorithm is used to learn the distribution of the quantity of interest in a structure with material nonlinearities and uncertainties. For the examples considered in this work, the data-driven cGANs model outperforms the physics-based approach. Finally, an example is shown where the two methods are coupled such that a hybrid model approach is demonstrated.

Impact Statement

In the current work, a generative model framework for digital twins is proposed. The framework is fitted to a mathematical formulation of digital twins, also referred to as mirrors, from the previous works. Different types of generative models are presented and tested on simulated data. The physics-based model is a stochastic finite element model, widely used to model structures under uncertainty. The data-driven method is a conditional adversarial network, whose functionality fits the framework of mirrors. The hybrid-model is the combination of the two aforementioned methods. All models are tested according to their ability to model uncertainty. Finally, the models are considered as two different types of mirrors, ε-mirrors and α-mirrors, which have different functionality.

1. Introduction

A recent innovation in the field of system simulation is the creation of *digital twins* for specific systems (called physical twins). For example, attempts have been made to do this in the fields of manufacturing (Rosen et al., 2015; Uhlemann et al., 2017), control systems and the internet of things (Schluse et al., 2018), smart cities (Dembski et al., 2020), social networks, and management (Macchi et al., 2018)—more

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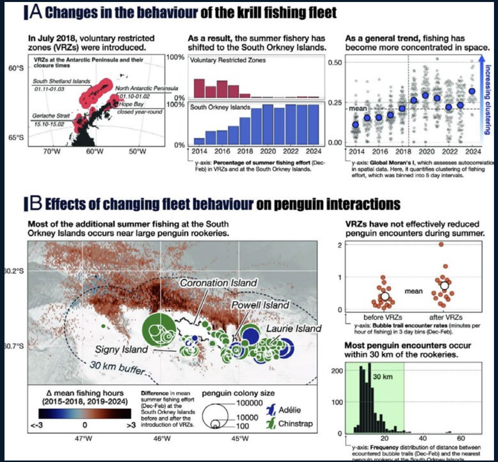
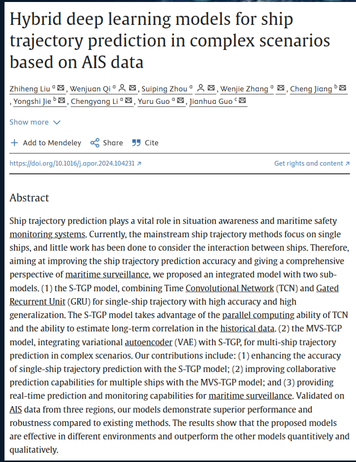
Tsialiamanis, G. *et al.* (2021) 'On generative models as the basis for digital twins', *Data-Centric Engineering*, 2, p. e11. doi:10.1017/dce.2021.13.



Bahlburg, D., Menze, S., Krafft, B. A., Lowther, A. D., & Meyer, B. (2025). Mapping encounters between Antarctic krill fishing vessels and air-breathing krill predators using acoustic data from the fishery. Proceedings of the National Academy of Sciences of the United States of America, 122(25), e2417203122. https://doi.org/10.1073/pnas.2417203122



Hybrid deep learning models for ship trajectory prediction in complex scenarios based on AIS data

Zhiheng Liu [a], Wenjuan Qi [a], Suiping Zhou [a], Wenjie Zhang [a], Cheng Jiang [b], Yongshi Jie [b], Chengyang Li [a], Yuru Guo [a], Jianhua Guo [c]

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Abstract

Ship trajectory prediction plays a vital role in situation awareness and maritime safety monitoring systems. Currently, the mainstream ship trajectory methods focus on single ships, and little work has been done to consider the interaction between ships. Therefore, aiming at improving the ship trajectory prediction accuracy and giving a comprehensive perspective of maritime surveillance, we proposed an integrated model with two sub-models. (1) the S-TGP model, combining Time Convolutional Network (TCN) and Gated Recurrent Unit (GRU) for single-ship trajectory with high accuracy and high generalization. The S-TGP model takes advantage of the parallel computing ability of TCN and the ability to estimate long-term correlation in the historical data. (2) the MVS-TGP model, integrating variational autoencoder (VAE) with S-TGP, for multi-ship trajectory prediction in complex scenarios. Our contributions include: (1) enhancing the accuracy of single-ship trajectory prediction with the S-TGP model; (2) improving collaborative prediction capabilities for multiple ships with the MVS-TGP model; and (3) providing real-time prediction and monitoring capabilities for maritime surveillance. Validated on AIS data from three regions, our models demonstrate superior performance and robustness compared to existing methods. The results show that the proposed models are effective in different environments and outperform the other models quantitatively and qualitatively.

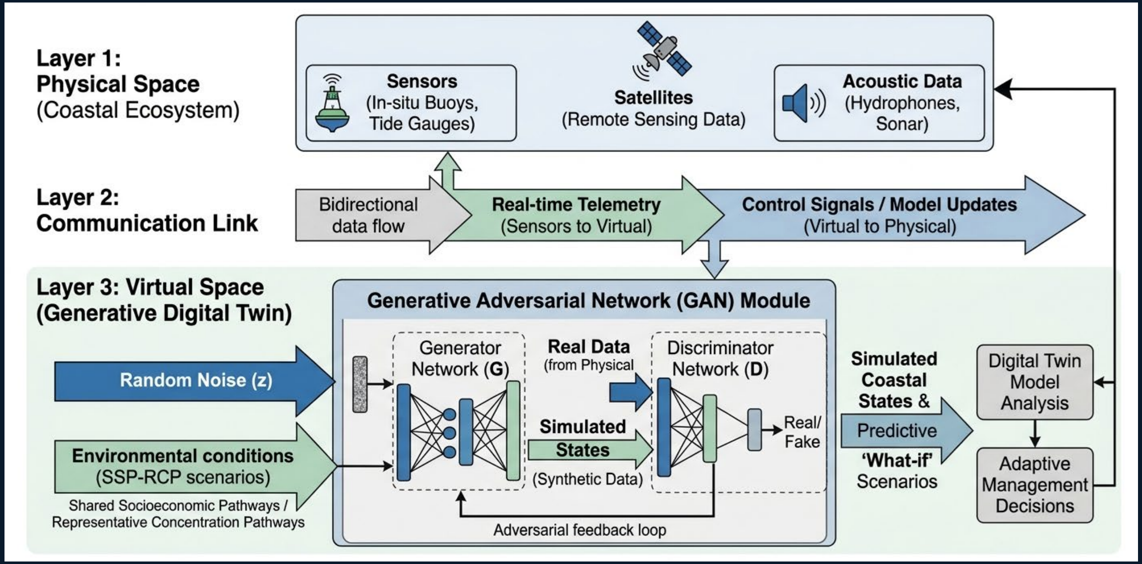
Zhiheng Liu, Wenjuan Qi, Suiping Zhou, Wenjie Zhang, Cheng Jiang, Yongshi Jie, Chengyang Li, Yuru Guo, Jianhua Guo,
Hybrid deep learning models for ship trajectory prediction in complex scenarios based on AIS data, Applied Ocean Research, Volume 153, 2024, 104231, ISSN 0141-1187,

Proactive vs. Reactive: Managing 'trigger levels' before they occur.

Data Scarcity: Leveraging 'data-rich' regions to mirror 'data-poor' ones.

Uncertainty: Moving from single points to probabilistic distributions.

Proposed Framework (Methodology)



Case Study I: Jiaodong Peninsula

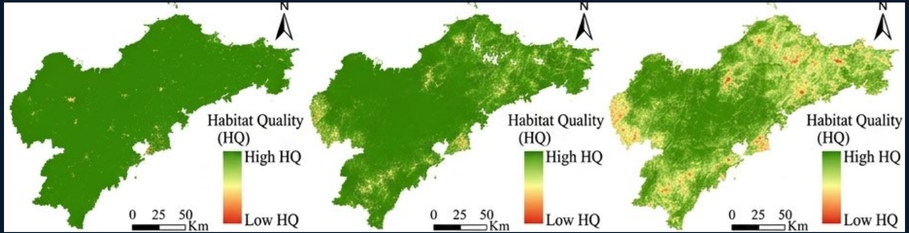


Fig 1: Habitat Quality: 2000 (Baseline); Fig 2: Habitat Quality: 2020 (Historical Ground Truth); Fig 3: Habitat Quality: 2050 (GAN-projected, SSP5-8.5)

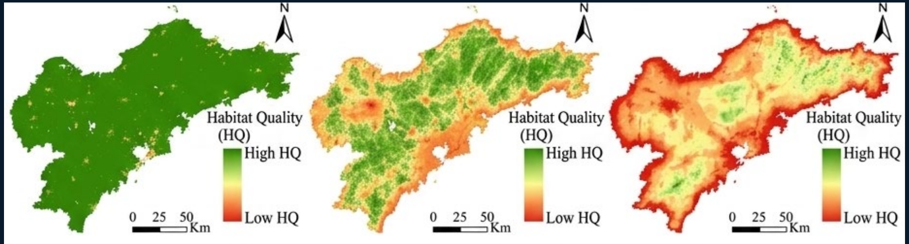


Fig 4: Habitat Quality Projections for 2050 (GAN-Projected, SSP5-8.5)

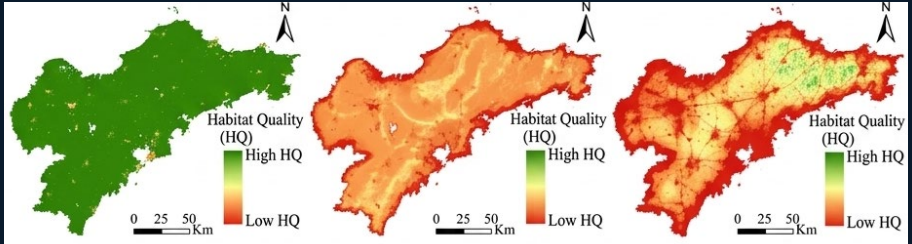
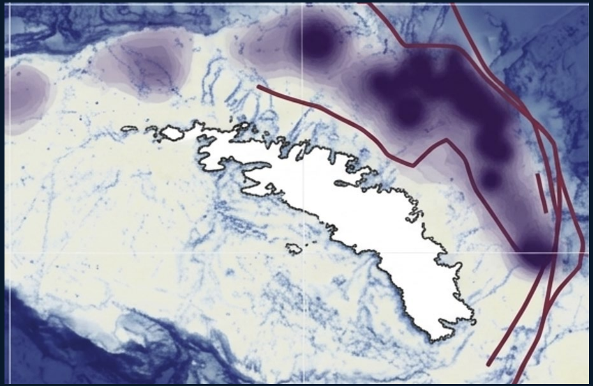


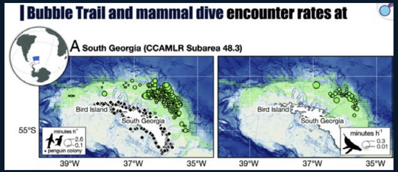
Fig 5: Habitat Quality Projections for 2050 (GAN-Projected, SSP5-8.5)

Case Study II: Southern Ocean Interactions



The continuous probability cloud (purple heat-map) defines the overall foraging zone probability, replacing individual rate circles for a smoother representation of spatial use. The vessel tracks (red lines) are overlaid to show intersection with foraging areas.



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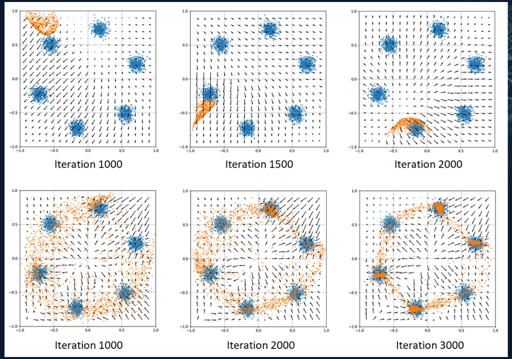
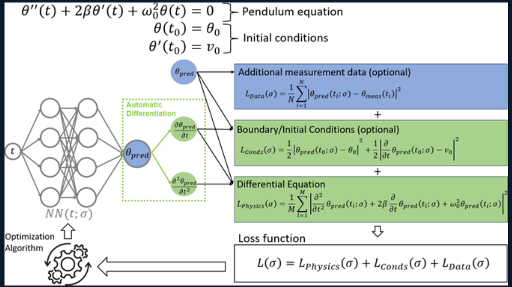
Limitations & Next Steps

Mode Collapse: Risks in GAN training.

Physics Gap: Ensuring mass conservation and hydrodynamics (PINNs).

XAI: Making the 'Black Box' explainable for policy makers. (CITL; Community in the loop)





Q+A