

Physically-Consistent Generative Adversarial Networks for Coastal Flood Visualization

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As climate change increases the intensity of natural disasters, society needs better tools for adaptation. Floods, for example, are the most frequent natural disaster, and better tools for flood risk communication could increase the support for flood-resilient infrastructure development. Our work aims to enable more visual communication of large-scale climate impacts via visualizing the output of coastal flood models as satellite imagery. We propose the first deep learning pipeline to ensure physical-consistency in synthetic visual satellite imagery. We advanced a state-of-the-art GAN called pix2pixHD, such that it produces imagery that is physically-consistent with the output of an expert-validated storm surge model (NOAA SLOSH). By evaluating the imagery relative to physics-based flood maps, we find that our proposed framework outperforms baseline models in both physical-consistency and photorealism. We envision our work to be the first step towards a global visualization of how climate change shapes our landscape. Continuing on this path, we show that the proposed pipeline generalizes to visualize arctic sea ice melt. We also publish a dataset of over 25k labelled image-pairs to study image-to-image translation in Earth observation¹.

Index Terms—Physics-Informed Neural Networks, Generative Adversarial Networks, Synthetic Data Generation, Climate Change, Flood Inundation Models, Visualization.

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¹Code and data will be open-sourced at gitlab.com/frontierdevelopmentlab/fdl-us-2020-earth-engine upon publication; an interactive demo is available at trillium.tech/eie.



Fig. 1: The *Earth Intelligence Engine* generates physically-consistent satellite imagery of future coastal flood events to aid in climate communication. Explore more results in high-resolution at trillium.tech/eie.

I. INTRODUCTION

Our climate changes, causing natural disasters to become more intense [1]. Floods are the most frequent weather-related disaster [2] and already cost the U.S. 3.7 B USD per year [3]; this damage is projected to grow over the next decades [1]. Visualizations of climate impacts are widely used by policy and decision makers to raise environmental awareness and facilitate dialogue on long-term climate adaptation decisions [4]. Current visualizations of coastal flood impacts, however, are limited to color-coded flood maps [5] or synthetic street-view imagery [6], which do not convey city-wide flood impacts in a compelling manner, as shown in Fig. 2 and [7]. Our work generates synthetic satellite imagery of future coastal floods, informed by the projections of expert-validated flood models, to enable a more engaging communication of city-wide flood risks to governmental offices.

Generative adversarial networks (GANs) have been used to generate highly photorealistic imagery of faces [12], [13], animals [14], [15], or even street-level flood imagery [10]. Recent works, have adapted GANs to generate satellite imagery [16], [17], [18], [19], [20]. Synthetic satellite imagery, however, needs to be trustworthy [21]. While many approaches exist to increase the trustworthiness of neural network-based models, including interpretable networks [22], adversarial robustness [23], [24], or ensemble predictions [25], [26], this work focuses on ensuring physical-consistency.

Many recent works incorporate domain knowledge from the physical sciences into deep learning [27], [28], [29], [30]. Our



Fig. 2: **Physically-consistent satellite imagery (c) could enable more engaging and relatable communication of city-scale flood risks [4]**. Most existing visualizations of coastal floods or sea-level rise that are aimed towards the public rely on color-coded geospatial rasters (a), that can be unrelatable or impersonal [5], [8], [9]. Alternative photorealistic visualizations are often limited to local street-level imagery (b) [6], [10] that lack further spatial context. Image sources: [5], [5], [6], [6], [11], ours.

work aims to generate physically-consistent imagery, whereas we define an image as physically-consistent if it depicts the same flood extent as an expert-validated coastal flood model, as detailed in Section III-C. To achieve physical-consistency, one could adapt the neural network architecture to incorporate physics as: inputs [31], training loss [32], the learned representation [33], [34], [22], hard output constraints [35], or evaluation function [36]. Alternatively, one could embed the neural network in differential equations [37], for example, as: parameters [38], [32], dynamics [39], residual [40], [41], differential operator [27], [42], or solution [32]. Our work is the first in leveraging any of these methods to ensure physical-consistency in synthetic visual satellite imagery, to the extent of the authors' knowledge. Specifically, our work leverages years of scientific domain knowledge by incorporating physics-based coastal flood model projections as neural network input and evaluation function. Exploring the alternative forms of physical consistency for satellite imagery is an exciting field left for future works.

Our work makes five contributions:

- the first generative vision pipeline to generate physically-consistent visual satellite imagery for hypothetical scenarios, called the *Earth Intelligence Engine*,
- the first physically-consistent and photorealistic visualization of coastal flood models as satellite imagery,
- a novel metric, the Flood Visualization Plausibility Score (FVPS), to evaluate the photorealism and physical-consistency of generated imagery, and
- the demonstration of a *climate impact visualization* pipeline on coastal floods and melting Arctic sea ice,
- an open-source dataset with over 25k labelled high-resolution image-pairs to study image-to-image translation in Earth observation.

II. RELATED WORK

Our work combines a coastal flood model with a generative vision model in a novel physically-consistent pipeline to create visualizations of coastal floods.

A. Generative vision modeling.

We aim to learn the change in satellite imagery from before to after a coastal flood, which is similar to paired image-

to-image translation [12]. Within image-to-image translation models, generative adversarial networks (GANs) generated samples of highly photorealistic imagery. For example, semantic image synthesis models generated photorealistic street scenery from semantic segmentation masks: DCGAN [43], Pix2pixHD [13], DRGAN [44], SPADE [45], or OASIS [46]. In comparison to GANs, normalizing flows [47], [26] or variational autoencoders [48] capture the distribution of possible image-to-image translations more accurately [49], but single samples often look less realistic ([50], [51], Fig. 4). Because our use case requires photorealism we focus on GANs and extend the high-resolution semantic image synthesis model, pix2pixHD [13], to take in physical information and produce imagery that is both photorealistic and physically-consistent. We leave ensemble predictions capturing the full distribution of images for future work.

B. Physics-informed deep learning.

Physics-informed deep learning has recently generated significant excitement. It promises to increase trust, interpretability, and data-efficiency of deep learning models [27], [28], [31]. The *Earth Intelligence Engine* incorporates a physics-based coastal flood model as input and evaluation function and is the first in the physics-informed deep learning literature to generate physically-consistent satellite imagery [31]. Future works will extend the connections between physics and deep learning-generated satellite imagery. For example, [52] could be used to learn a physically-interpretable latent space, e.g., a “flood neuron”, [53] to embed deep learning in atmospheric noise models, or [46] to incorporate physics-based flood maps in the loss function.

C. Climate change visualization tools

Visualizations of climate change are commonly used in policy making and community discussions on climate adaptation [4], [54]. Landscape visualizations are used to raise environmental awareness in the general public or policy [7], [10], because they can convey the impacts of climate change, such as rising sea levels or coastal floods, in a compelling and engaging manner ([7], Fig. 2b). Most landscape visualizations, however, are limited to regional information [6]. Additionally,

most landscape visualizations require expensive physics-based renderings and/or high-resolution digital elevation models [6]. Alternative visualization tools of coastal floods or sea-level rise are color-coded maps, such as [55], [5], [9]. Color-coded maps convey the flood extent on a city-wide scale, but are less engaging than a photorealistic image [4]. We are generating compelling visualizations of future coastal floods as satellite imagery to aid in policy and community discussion on climate adaptation.

III. APPROACH

The proposed pipeline uses a generative vision model to generate post-flood images from pre-flood images and a flood extent map, as shown in Fig. 3.

A. Data Overview.

Obtaining ground-truth post-flood images that display standing water is challenging due to cloud-cover, time of standing flood, satellite revisit rate, increased atmospheric noise, and cost of high-resolution imagery. This work leverages the xBD dataset [11], a collection of pre- and post-disaster images from events like Hurricane Harvey or Florence, from which we obtained ~ 3 k pre- and post-flood image pairs with the following characteristics: ~ 0.5 m/px, RGB, 1024×1024 px/img, Maxar DigitalGlobe.

The coastal flood model is the *Sea, Lake and Overland Surges from Hurricanes* (SLOSH) model [56], developed by the National Weather Service (NWS). SLOSH estimates storm surge heights from atmospheric pressure, hurricane size, forward speed, and track data, which are used as a wind model driving the storm surge. The SLOSH model consists of shallow water equations, which consider unique geographic locations, features, and geometries. The model is run in deterministic, probabilistic, and composite modes by various agencies for different purposes, including NOAA, National Hurricane Center (NHC) and NWS. We use outputs from the composite approach – that is, running the model several thousand times with hypothetical hurricanes under different storm conditions. As a result, we obtain a binary flood hazard map from [5] as displayed in Fig. 2a which are storm-surge, height-differentiated, flood extents at 30 m/px resolution. The flood hazard maps do not intersect with the locations of existing post-flood imagery. To get around the data limitation, we generate and coarse-grain segmentation maps of the post-flood imagery to 30 m/px for training and evaluation and use binarized flood hazard maps during test. Future works will extend the state-of-the-art *Advanced CIRCulation* model (ADCIRC) [57] model, which is described in [8] and has a stronger physical foundation with better accuracy, and higher resolution than SLOSH.

B. Model architecture.

The central model of our pipeline is a generative vision model that learns the physically-conditioned image-to-image transformation from pre-flood image to post-flood image. We leveraged the existing implementation of pix2pixHD [13].

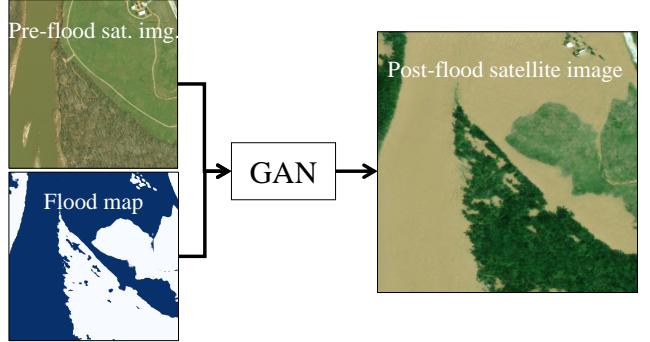


Fig. 3: Model Architecture. Our model leverages the semantic image synthesis model, Pix2pixHD [58], and combines a pre-flood satellite image with a physics-based flood map to generate post-flood imagery.

Pix2pixHD is a state-of-the-art semantic image synthesis model that uses multi-scale generator and discriminator architectures to generate high-resolution imagery. We extended the input dimensions to $1024 \times 1024 \times 4$ to incorporate the flood extent map. The resulting pipeline is modular, such that it can be repurposed for visualizing other climate impacts.

C. Physically-consistent image.

We define a *physically-consistent* model as one that fulfills laws of physics, such as, conservation of momentum, mass, and energy [28]. For example, most coastal flood models consist of numerical solvers that resolve the conservation equations to generate flood extent predictions [56]. Here, we consider an image to be physically-consistent if it depicts the predictions of a physically-consistent model.

Specifically, we define our generated satellite imagery, $I_G \in \mathcal{I} = [0, 1]^{w \times h \times c}$ with width, $w = 1024$, height, $h = 1024$, and number of channels, $c = 3$, to be physically-consistent if it depicts the same flood extent as the binary flood map, $F \in \mathcal{F} = \{0; 1\}^{w \times h}$. We implemented a flood segmentation model, $m_{\text{seg}} : \mathcal{I} \rightarrow \mathcal{F}$, to measure the depicted flood extent in the generated image. If the flood extent of a generated image and the coastal flood model match within a margin, the image is in the set of physically-consistent images, i.e., $I_{\text{phys}} \in \mathcal{I}_{\text{phys}} = \{I_G \in \mathcal{I} : \text{IoU}(m_{\text{seg}}(I_G), F) < \epsilon\}$. The generated image is considered photorealistic, if it is contained in the manifold of naturally possible satellite images, $I_{\text{photo}} \in \mathcal{I}_{\text{photo}} \subset \mathcal{I}$. Hence, we are looking for a conditional image generation function, g , that generates an image that is both, physically-consistent and photorealistic, i.e, $g : \mathcal{I}_{\text{photo}} \times \mathcal{F} \rightarrow \mathcal{I}_{\text{photo}} \cap \mathcal{I}_{\text{phys}}$. Here, we condition the GAN on the flood map, F , and use a custom evaluation function to identify the generation function, g .

D. The Evaluation Metric Flood Visualization Plausibility Score (FVPS).

Evaluating imagery generated by a GAN is difficult [59], [60]. Most evaluation metrics measure photorealism or sample diversity [60], but not physical consistency [61] (see, e.g.,

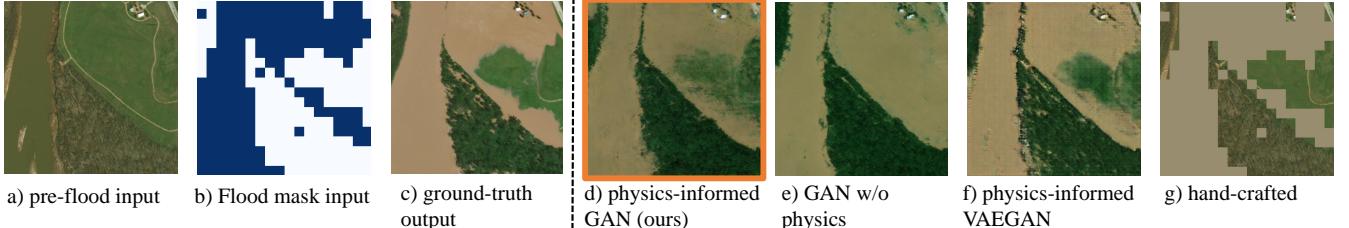


Fig. 4: The proposed physics-informed GAN, (d), generates photorealistic and physically-consistent flood imagery from the inputs, (a,b), outperforming all other models, (e,f,g). The baseline GAN, pix2pixHD [13] (e), in comparison, receives only a pre-flood image and no physical input. The resulting image, (e), is fully-flooded, rendering the model untrustworthy. The VAEGAN, BicycleGAN [51] (f), creates glitchy imagery (zoom in). A handcrafted baseline model (g), as used in common visualization tools [9], [55], visualizes the correct flood extent, but is pixelated and lacks photorealism.

SSIM [62], MMD [63], IS [64], MS [65], FID [66], [67], or LPIPS [68].

To evaluate physical consistency we propose using the intersection over union (IoU) between water in the generated imagery and water in the flood extent map. This method relies on flood masks, but because there are no publicly available flood segmentation models for Maxar RGB satellite imagery, we trained our own model on ~ 100 hand-labeled flooding images (Section IV-B). This segmentation model produced flood masks of the generated and ground-truth flood image which allowed us to measure the overlap of water in between both. When the flood masks overlap perfectly, the IoU is 1; when they are completely disjoint, the IoU is 0.

To evaluate photorealism, we used the state-of-the-art perceptual similarity metric Learned Perceptual Image Patch Similarity (LPIPS) [68]. LPIPS computes the feature vectors (of an ImageNet-pretrained AlexNet CNN architecture) of the generated and ground-truth tile and returns the mean-squared error between the feature vectors (best LPIPS is 0, worst is 1).

Because the joint optimization over two metrics poses a challenging hyperparameter optimization problem, we propose to combine the evaluation of physical consistency (IoU) and photorealism (LPIPS) in a new metric (FVPS), called Flood Visualization Plausibility Score (FVPS). The FVPS is the harmonic mean over the submetrics, IoU and $(1 - \text{LPIPS})$, that are both $[0, 1]$ -bounded. Due to the properties of the harmonic mean, the FVPS is 0 if any of the submetrics is 0; the best FVPS is 1. In other words, the FVPS is only 1 if the imagery is both photorealistic and physically-consistent.

$$\text{FVPS} = \frac{2}{\frac{1}{\text{IoU} + \epsilon} + \frac{1}{1 - \text{LPIPS} + \epsilon}}. \quad (1)$$

IV. EXPERIMENTAL RESULTS

A. Physical-consistency and photorealism.

In terms of both physical-consistency and photorealism, our physics-informed GAN outperforms an unconditioned GAN that does not use physics, as well as a handcrafted baseline model (Fig. 4).

1) *A GAN without physics information generates photorealistic but non physically-consistent imagery.*

The inaccurately modeled flood extent in Fig. 4e illustrates the physical-inconsistency and a low IoU of 0.226 in Table I

over the test set further confirms it (see Section A for test set details). Despite the photorealism ($\text{LPIPS} = 0.293$), the physical-inconsistency renders the model non-trustworthy for critical decision making, as confirmed by the low FVPS of 0.275. The model is the default pix2pixHD [13], which only uses the pre-flood image and no flood mask as input.

2) *A handcrafted baseline model generates physically-consistent but not photorealistic imagery.*

Similar to common flood visualization tools [9], the handcrafted model overlays the flood mask input as a hand-picked flood brown (#998d6f) onto the pre-flood image, as shown in Fig. 4g. Because typical storm surge models output flood masks at low resolution (30m/px [5]), the handcrafted baseline generates pixelated, non-photorealistic imagery. Combining the high IoU of 0.361 and the poor LPIPS of 0.415, yields a low FVPS score of 0.359, highlighting the difference to the physics-informed GAN in a single metric.

3) *The proposed physics-informed GAN generates physically-consistent and photorealistic imagery.*

To create the physics-informed GAN, we trained pix2pixHD [13] from scratch on our dataset (200 epochs in ~ 7 hrs on $8 \times \text{V100}$ Google Cloud GPUs). This model successfully learned how to convert a pre-flood image and a flood mask into a photorealistic post-flood image, as shown in Fig. 1. The model outperformed all other models in IoU (0.553), LPIPS (0.263), and FVPS (0.532) (Table I). The learned image transformation “in-paints” the flood mask in the correct flood colors and displays an average flood *height* that does not cover structures (e.g., buildings, trees), as shown in 64 randomly sampled test images in Fig. 5. Occasionally, city-scenes show scratch patterns, e.g., Fig. 5 (top-left). This could be explained by the unmodeled variance in off-nadir angle, sun inclination, GPS calibration, color calibration, atmospheric noise, dynamic objects (cars), or flood impacts, which is partially addressed in Section IV-C1. While our model also outperforms the VAEGAN (BicycleGAN), the latter has the potential to create ensemble forecasts over the unmodeled flood impacts, such as the probability of destroyed buildings.

B. Flood segmentation model.

The flood segmentation model was a pix2pix segmentation model [12], which uses a vanilla U-net as generator. The



Fig. 5: Generated post-flooding imagery of 64 randomly chosen tiles of hurricanes Harvey and Florence test set.

model was trained from scratch to minimize $L1$ -loss, IoU, and adversarial loss and had the last layers finetuned on $L1$ -loss. We hand-labelled pixel-wise flood maps of 111 post-flood images to train the model. A four-fold cross validation was performed leaving 23 images for testing. The segmentation model selected to be used by the FVPS has a mean IoU performance of 0.343. Labelled imagery will be made available as part of the dataset.

C. Generalization performance.

So far, we showed that our pipeline can generate post-flood imagery for the selected locations, such hurricane Harvey in Houston, TX, and for matching remote sensing instruments between train and test, e.g., Maxar satellite. The *Earth Intelligence Engine*, however, aims to visualize global climate change as seen from space, starting with a visualization of coastal floods and sea-level rise along the full U.S. East Coast. In order to achieve a visualization along the coast, the pipeline needs to generalize across locations, remote sensing instruments, and climate phenomena.

1) Generalization across location and remote sensing instruments.

To generalize across the U.S. East Coast, the current framework would require a Maxar pre-flood image mosaic, which would be costly and challenging to open-source for the full U.S. East Coast. Hence, we assembled a dataset of pre-flood image tiles from the open-access U.S.-wide mosaic of $1.0m/px$ visual aerial imagery from the National Agriculture Imagery Program (NAIP) [69]. The pre-flood NAIP image tiles are paired with open-access Maxar post-flood satellite imagery and a generated pixelwise flood segmentation mask. This creates a dataset of 6500 clean image-triplets that we are releasing as the floods-section of our open-source dataset to study image-to-image translation in Earth observation.

The translation task from NAIP aerial to Maxar satellite imagery is significantly more challenging than the Maxar \rightarrow Maxar task, because the learned image-transformation needs to account for differing remote sensing instruments, flight altitude, atmospheric noise magnitude, color calibration, and more. To reduce the learning task complexity, we removed the variation within Maxar data, via sourcing

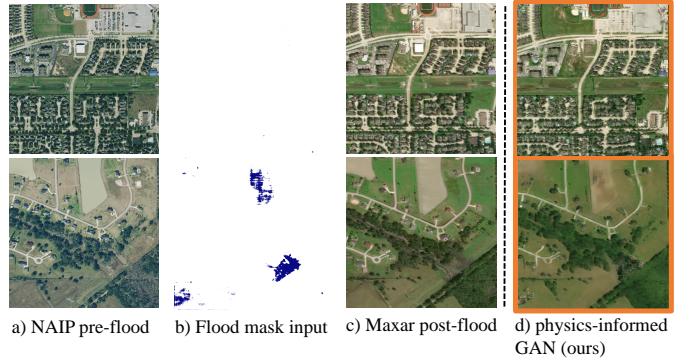


Fig. 6: Generalization across remote sensing instruments. We have compiled a dataset of 6500 image-pairs to generalize across remote sensing instruments, here predicting $0.5m/px$ Maxar satellite imagery (output) from $1.0m/px$ aerial NAIP imagery. The generated imagery (left) suggests that the model can learn across different remote sensing instruments, learning the change in resolution, flight altitude, color calibration, and atmospheric noise magnitude.

post-flood tiles from a single satellite pass over west Houston, TX on 8/31/2017, post-hurricane Harvey [70]. To re-run our pipeline, we labelled 260 flood segmentation masks (in ~ 2 hrs), retrained the flood segmentation model, and re-trained the physics-informed GAN from scratch on the new dataset (for 15 epochs in ~ 5 hrs on $1 \times V100$ GPU). The resulting model did not outperform the baseline in physical-consistency, which is likely due to the suboptimal performance of this dataset’s segmentation model ($\text{IoU}=0.23$). However, the resulting model still outperforms the baseline in photorealism ($\text{LPIPS}=0.369$ vs. 0.465) on a 20% test split. This shows that image-to-image translation across remote sensing instruments is feasible, as well as, the potential to leverage the *Earth Intelligence Engine* to create a visualization of coastal floods along the full U.S. East Coast.

2) Visualizing Arctic sea ice melt

The retreat of Arctic sea ice is one of the most important and imminent consequences of climate change [1]. However, visualizations of melting Arctic sea ice are limited to physics-based renderings, such as [71]. There is also a lack of daily visual satellite imagery of the past due to satellite revisit rate, cloud cover, or polar night. The *Earth Intelligence Engine* is envisioned to create visualizations of past and future melting Arctic sea ice.

We assembled a dataset with $\sim 20k$ 1024×1024 px image-pairs of high-resolution ($10m/px$) visual Sentinel-2 imagery, as showcased in Fig. 7. We leveraged ice-free tiles from the temporary Arctic summer (1/6 – 31/8/2020) as training data to generate ice-free visual satellite imagery. Each ice-free summer tile is associated with a corresponding winter (1/10 – 1/5/2020) tile from the same area. We ensured image diversity in land, ocean, and ice tiles by sampling Arctic coastal regions and removing image duplicates with perceptual hashing. Ice segmentation masks were generated for each summer tile by classifying each pixel with normalized

	LPIPS high res.	LPIPS low res.	IoU high res.	LPIPS low res.	FVPS high res.	FVPS low res.
GAN w/ phys. (ours)	0.265	0.283	0.502	0.365	0.533	0.408
GAN w/o phys.	0.293	0.293	0.226	0.226	0.275	0.275
VAEGAN w/ phys.	0.449	-	0.468	-	0.437	-
Handcrafted baseline	0.399	0.415	0.470	0.361	0.411	0.359

TABLE I: In terms of photorealism (LPIPS) and physical consistency (IoU), our physics-informed GAN outperforms three benchmarks: the baseline GAN without physics; a physics-informed VAEGAN; and a handcrafted baseline. The proposed Flood Visualization Plausibility Score (FVPS) trades-off IoU and LPIPS as a harmonic mean and highlights the performance differences between the GAN with and without physics on low-resolution flood mask inputs.

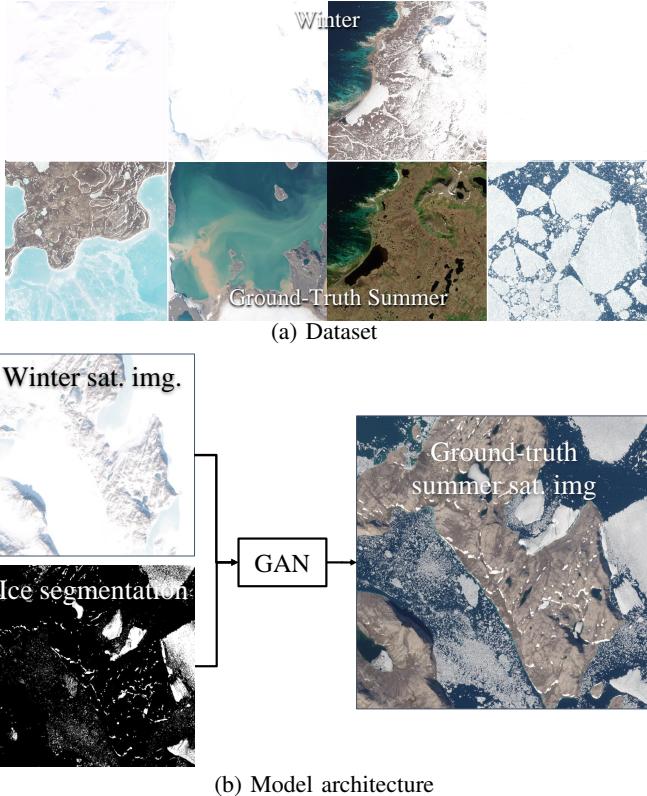


Fig. 7: We compiled a dataset of $\sim 20k$ image-pairs of the Arctic to visualize melting Arctic sea ice.

grayscale value, $i > 0.7$, as ice. The image-triplets are then used to retrain the *Earth Intelligence Engine* using the same hyper-parameters and configuration used in predicting floods. We acknowledge that predictions of Arctic sea ice extent only exist at low-resolution (e.g., ~ 6 km in the Modèle Atmosphérique Régional, MAR) while our framework leverages high-resolution masks. Future works will leverage coarse-grained masks during training to fully extend the framework to visualize future melting of Arctic sea ice as projected by MAR.

V. DISCUSSION AND FUTURE WORK

1) Limitations.

Although our pipeline outperformed all baselines in the generation of physically-consistent and photorealistic imagery of coastal floods, there are areas for improvement in future

works. For example, our flood datasets only contained 3 or $6.5k$ samples and were biased towards vegetation-filled satellite imagery; this data limitation likely contributes to our model rendering human-built structures, such as streets and out-of-distribution skyscrapers in Fig. 5 top-left, as smeared. Although we attempted to overcome our data limitations by using several state-of-the-art augmentation techniques, this work would benefit from more public sources of high-resolution satellite imagery (augmentation details in Section B). Apart from the data limitation, smeared features are still a current concern in state-of-the-art GAN architectures [46]. Furthermore, the computational intensity of training GANs made it difficult to optimize the models on new data. Improved transfer learning techniques could address this challenge. Lastly, satellite imagery is an internationally trusted source for analyses in deforestation, development, or military domains [72], [73]. With the increased capability of data-generating models, more work is needed in the identification of and the education around misinformation and ethical and trustworthy AI [21]. We point out that our satellite imagery is synthetic, should only be used as communication aid [4], and we take first steps towards guaranteeing trustworthiness in synthetic satellite imagery.

2) Cloud-penetrating satellite imagery.

Remote sensing commonly faces the problem of missing frames, due to cloud-cover, orbital alignment, or cost of high-resolution imagery [74], [75]. The *Earth Intelligence Engine* can be seen as a gap-filling model that combines the information from low-resolution flood maps and high-resolution pre-flood image mosaics to infer the missing high-resolution post-flood satellite imagery. For example after floods, the arrival of the first visual images is often delayed until clouds pass or expensive drone surveys are conducted. Synthetic-aperture radar (SAR) is cloud-penetrating and often returns the first available medium-resolution flood maps (at ~ 10 m/px) [76]. The *Earth Intelligence Engine* could visualize the medium-resolution SAR-derived flood extent maps. However, future work will be necessary to extend the trustworthiness of generated flood visualizations in disaster response, for example, via incorporating information on the flood height, building damage, or the raw SAR signal. The current visualizations are aimed towards media or policy to communicate the possible extent of future floods in a compelling manner [4].

3) Vision for the future.

We envision a global visualization tool for climate impacts. By changing the input data, future work can visualize impacts of other well-modeled, climate-attributed events, including Arctic sea ice melt, hurricanes, wildfires, or droughts. Non-binary climate impacts, such as inundation height, or drought strength could be generated by replacing the binary flood mask with continuous model predictions. Opportunities are abundant for further work in visualizing our changing Earth. This work opens exciting possibilities in generating physically-consistent imagery with potential impact on improving climate mitigation and adaptation.

March 12, 2021

VI. ACKNOWLEDGEMENTS

This research was conducted at the Frontier Development Lab (FDL), US. The authors gratefully acknowledge support from the MIT Portugal Program, National Aeronautics and Space Administration (NASA), and Google Cloud.

We are very thankful for Margaret Maynard-Reid and Leo Silverberg for generating the demo at trillium.tech/eie. We thank Ritwik Gupta for the continuous help in using the xBD dataset, Richard Strange for the help with cloud compute, Prof. Marco Tedesco for advise on the Arctic sea ice, Guy Schumann on flood modeling, Mark Veillette and Cait Crawford for technical direction, and James Parr, Leah Lovgren, Sara Jennings and Jodie Hughes for the organization of FDL and enabling these connections. We greatly appreciate the advise on decision-/policymaking in coastal climate adaptation by Derek Loftis, Sagy Cohen, Capt. John Radovan, Maya Nasr, and Janot Mendler de Suarez. Further, we greatly appreciate the technical feedback and direction from Esther Wolff, Hannah Munguia-Flores, Peter Morales, Nicholas Mehrle, Prof. Bistra Dilkina, Freddie Kalaitzis, Graham Mackintosh, Michael van Pohle, Gail M. Skofronick-Jackson, Tsengdar Lee, Madhuli Guhathakurta, Julien Cornebise, Maria Molina, Massy Mascaro, Scott Penberthy, John Karcz, Jack Kaye, Campbell Watson, and all other FDL researchers.

The research was partially sponsored by the United States Air Force Research Laboratory and the United States Air Force Artificial Intelligence Accelerator and was accomplished under Cooperative Agreement Number FA8750-19-2-1000. The views and conclusions contained in this document are those of the authors and should not be interpreted as representing the official policies, either expressed or implied, of the United States Air Force or the U.S. Government. The U.S. Government is authorized to reproduce and distribute reprints for Government purposes notwithstanding any copyright notation herein.

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APPENDIX A DATASET

A. Pre- and post-flood imagery

Post-flood images that display standing water are challenging to acquire due to cloud-cover, time of standing flood, satellite revisit rate, and cost of high-resolution imagery. To the extent of the authors’ knowledge, xBD [\[11\]](#) is the best publicly available data-source for preprocessed high-resolution imagery of pre- and post-flood images. More open-source, high-resolution, pre- and post-disaster images can be found in unprocessed format on DigitalGlobe’s Open Data repository [\[77\]](#).

- Data Overview: 3284 flood-related RGB image pairs from seven flood events at 1024×1024 px of ~ 0.5 m/px resolution of which 30% display a standing flood (~ 1370).
- The dataset contains imagery of hurricanes (Harvey, Florence, Michael, Matthew in the U.S. East or Gulf Coast), spring floods (2019 in Midwest U.S.), a tsunami (in Indonesia), and the monsoon (in Nepal).
- Our evaluation test set is composed of 216 images: 108 images of each hurricane Harvey and Florence. The test

set excludes imagery from hurricane Michael or Matthew, because the majority of tiles does not display standing flood.

- We did not use digital elevation maps (DEMs), because the information of low-resolution DEMs is contained in the storm surge model and high-resolution DEMs for the full U.S. East Coast were not publicly available.

APPENDIX B EXPERIMENTS

A. Data Augmentation.

Standard data augmentation, here rotation, random cropping, hue, and contrast variation, and state-of-the art augmentation - here elastic transformations [\[78\]](#) - were applied. Furthermore, spectral normalization [\[79\]](#) was used to stabilize the training of the discriminator. A relativistic loss function has been implemented to stabilize adversarial training. We also experimented with training pix2pixHD on LPIPS loss. Quantitative evaluation of these experiments, however, showed that they did not have significant impact on the performance and, ultimately, the results in the paper have been generated by the pytorch implementation of pix2pixHD [\[13\]](#) extended to 4-channel inputs.

B. Pre-training LPIPS on satellite imagery.

The standard LPIPS did not clearly distinguish in between the handcrafted baseline and the physics-informed GAN, contrasting the opinion of a human evaluator. This is most likely because LPIPS currently leverages a neural network that was trained on object classification from ImageNet. The neural network might not be capable to extract meaningful high-level features to compare the similarity of satellite images. In preliminary tests the ImageNet-pretrained network would classify all satellite imagery as background image, indicating that the network did not learn features to distinguish satellite images from each other. Future work, will use LPIPS with a network trained to have satellite imagery specific features, e.g., Tile2Vec or a land-use segmentation [\[80\]](#) model.



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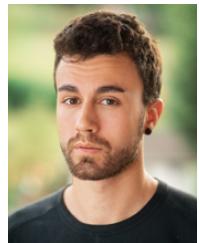
climate projections and physically-consistent GANs for visualizing coastal floods. He is also monitoring forest carbon from aerial imagery, which is supported by Microsoft, NASA, WWF, MIT PKG, MIT Legatum, and MIT Sandbox. He has previously obtained his M.Sc at MIT in Autonomous Systems, pioneering with Prof. Jon How safe and robust deep reinforcement learning techniques. More information available at lutjens.scripts.mit.edu/me.



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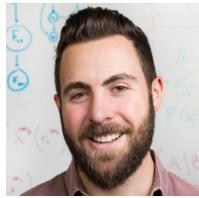
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Chedy Raïssi received his PhD in Computer Science from the Ecole des Mines d'Ales in July 2008. After completing his PhD, Chedy worked as a research fellow (post-doctoral researcher) at the National University of Singapore on privacy-preserving data mining with emphasis on the anonymization of clinical trial data. In 2010, Chedy was appointed as a permanent research scientist (chargé de recherche) at the French Institute for Research in Computer Science and Automation (INRIA), France where he joined the Orpailleur team and worked in the field of sequence and graph combinatorics and concept lattices (also known as “Galois lattices”). Since 2019, Chedy is on a sabbatical leave from INRIA and joined Ubisoft Singapore as the Data Science Director where he leads a new team of researchers and engineers to shape up innovative projects for machine learning and video games.



Alexander Lavin spent much of his career at the intersection of AI and neuroscience. He founded Latent Sciences to develop a patented AI platform (i.e. a probabilistic programming domain-specific language he built) for predictive and causal modeling neurodegenerative diseases, which was acqui-hired into a stealth enterprise AI company. Prior to Latent Sciences, he worked with Vicarious and Numenta towards artificial general intelligence. Prior to pursuing AI, he was a spacecraft engineer, working with NASA, Blue Origin, Astrobotic, and Technion. He is a technical lead with [nasa.ai](#) for various ML projects in climate science and astronaut health, and leading novel initiatives in Systems ML and a Forbes 30 Under 30 honoree in Science. He studied computational mechanics and robotics at Carnegie Mellon (under advisors Red Whittaker and Kenji Shamada), engineering management at Duke University, and mechanical and aerospace engineering at Cornell. Away from the computer he is a runner, yogi, outdoors explorer, and dog dad. More information available at [lavin.io](#).



Dava Newman is the Apollo Program Professor of Astronautics and Director of the MIT-Portugal Program at the Massachusetts Institute of Technology, and a Harvard-MIT Health, Sciences, and Technology faculty. Her aerospace biomedical engineering research investigates human performance across the spectrum of gravity, including space suits, life support and astronaut performance. She has been the PI on 4 spaceflight missions. Her second skin Bio-Suit™planetary spacesuit inventions are now being applied to soft exoskeletons to enhance locomotion on Earth. She has exhibited the BioSuit™at the Venice Biennial, London's Victoria and Albert Museum, Paris' Cite des Sciences et de L'Industrie, American Museum of Natural History, and Metropolitan Museum of Art. Her current research targets climate change and Earth's vital signs from Oceans-to-Space. She has circumnavigated, sailing around the world. She is the PI on the Earth Intelligence Engine AI platform for weather and climate. Newman is the author of the text Interactive Aerospace Engineering and Design and has over 300 publications. Dr. Newman served as NASA Deputy Administrator from 2015–2017, and was responsible for articulating NASA's vision, providing leadership and policy direction, spear-heading diversity and inclusion, and representing NASA to the White House, Congress, international space agencies, and industry. Dr. Newman was the first female engineer and scientist to serve in this role and was awarded the NASA Distinguished Service Medal.