

# Flood and Wildfire Simulations

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# Chapters

- **Natural Disaster Management (NDM)**
- Simulations of Forests Fires and Floods
- UAVs and Mission Planning
- Annotated Dataset Creation
- DNN Training and Results

# Natural Disaster Management



***Natural Disaster Management (NDM)*** examples:

- forest fires, floods.

Challenges in **NDM**:

- Acquisition of high-quality data proves to be a challenging issue due to the infrequent nature of the disasters and the logistical issues surrounding them
- Annotation of such data can be a costly and time-consuming task
- Training **Deep Neural Networks (DNNs)** for **NDM** (prediction, detection, etc.) requires not only large amounts of data but also data with high variety and veracity.

# Natural Disaster Management



**Natural Disasters** is a global issue, and many resources are invested into developing tools, strategies, etc. to minimize the damages caused.

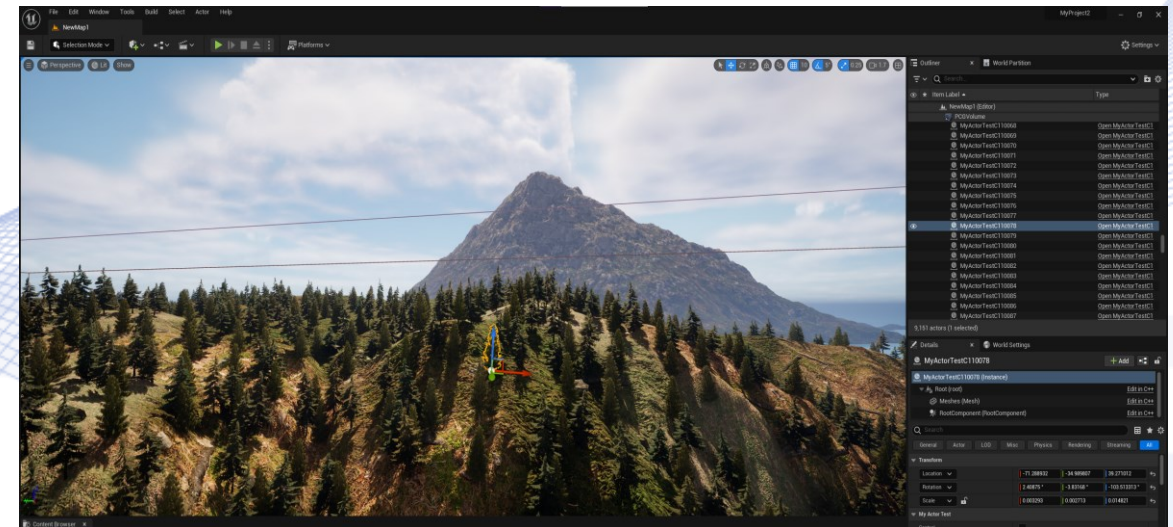
This work's focus is the development of tools for Forest Fires and Floods, simulations and visualizations, to create annotated synthetic image dataset for effective DDN training for tasks like **fire detection** and **fire - flood - burnt area segmentation**.

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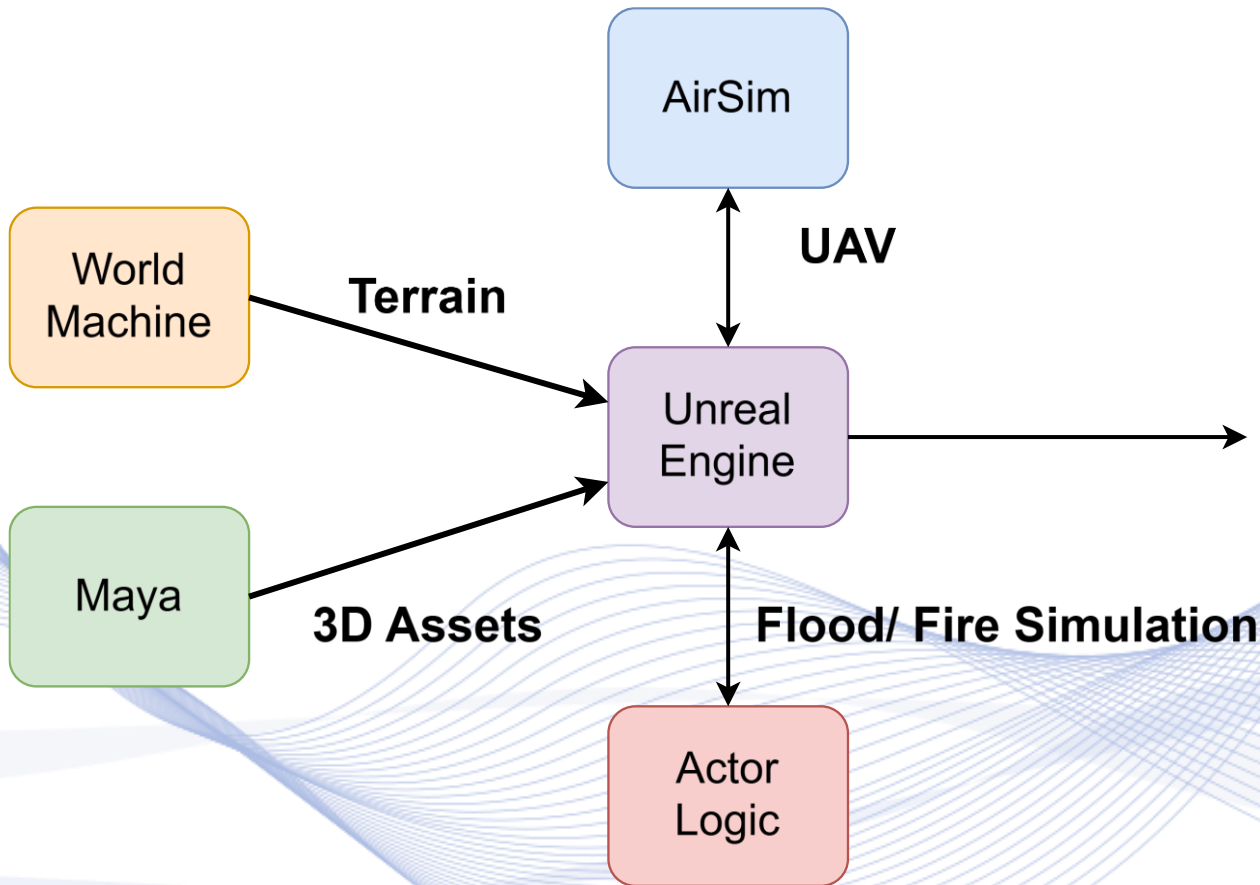
# Unreal Engine 5

- **Unreal Engine 5**, is an industry-leading platform in the field of game creation as well as film, architecture and more.
- Its photorealistic environments leverages advanced hardware capabilities (e.g., Raytracing) and combined with the scripting freedom of C++, we simulate **Natural Disasters** with relatively easy in a variety of scenery ( weather conditions, landscapes etc.)

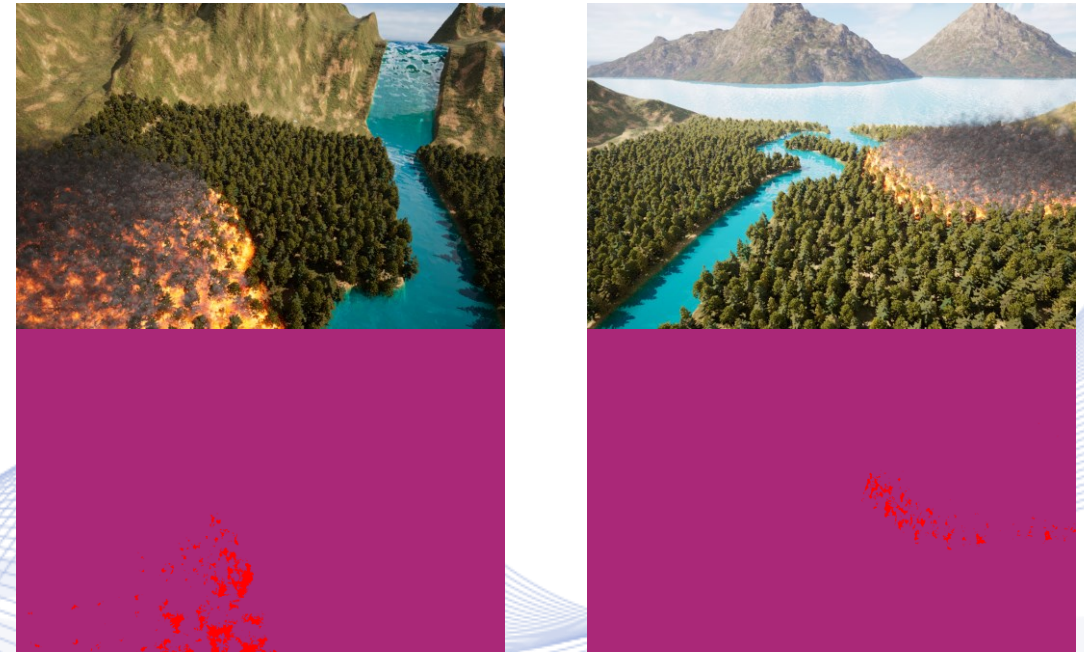


*Snapshot of the Unreal Engine Editor*

# Unreal Engine 5



- RGB – Mask Pairs



*RGB – MASK pairs of Fire scenario*

# Unreal Engine 5

- **World Machine** can be used to model a high-detail plane with hills and valleys, using a mixture of noises and manual modeling to create a real-world resembling terrain.
- **AutoDesk Maya** is the standard in 3D modeling and enables the creation of high-quality assets resembling a plethora of objects (e.g. trees, building, cars, etc.).

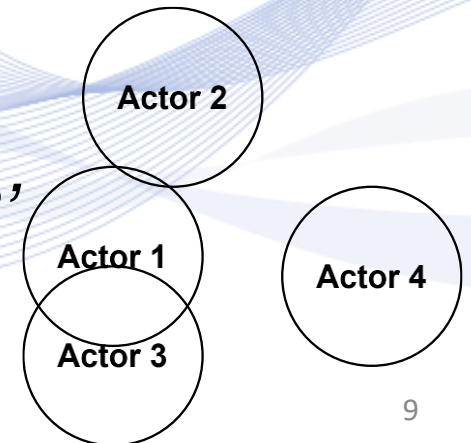


# Simulation of Wildfire

Every burnable object (trees, bushes etc.) is an actor with internal logic to control the parameters of the fire. All objects start of without fire and from a specific or random starting location, the fire spreads throughout the scene.

Each actor has a sphere with **hyper-parametrized** radius and every other actor's sphere colliding with it, is known to the actor, thus the actor can spread fire to them.

*Actors that Actor 1 can interact with = 'Actor 2, Actor 3'*



# Simulation of Wildfire

The intensity and behavior of the Wildfire is controlled by a plethora of hyperparameters and an abstract value '*Temperature*' that is used to control the fire of a specific object calculated by a scaled summation of the '*Temperatures*' of its neighbors.

*Some hyperparameters are:*

- An abstract value representing the flammability of the object
- Wind direction
- Rise speed
- Decay speed
- Start '*Temperature*'
- *Etc.*

# Simulation of Floods

For the flood scenarios, we use the '**Water Material**' plug-in that comes with Unreal Engine 5. It support full customization ( shape of the water body, color, flow, waves, etc.), so we can create synthetic environments resembling any real-world disaster.

In a similar manner with the fire, every object that we want to interact with the flood, is an Actor with hyper-parametrized behavior.

Some hyperparameters are: if the object should be moved by the water, how fast should it moved based on the flow speed of the water, if it floats, etc.

# Procedural Content Generation



To build large and varying worlds efficiently, we take advantage of the '**Procedural Content Generation (PCG)**' tool that Unreal Engine 5 offers.

It uses, Unreal's '**Blueprint Visual Scripting**', to create different settings for generating actors and props/meshes in a scene using hyperparameters such as:

- Density (for desired Actor or Mesh)
- Spacing between Actors/Meshes of the same type
- Random Scaling – Rotations
- Etc.

# World Building



## River Scenario:

- *Sparse trees*
- *Flat main terrain*
- *Water Bodies*

## Snow Scenario:

- *Dense trees*
- *Terrain with small bumps*
- *Snow on the ground*

# World Building



## Urban Flood Scenario:

- *Dark shade of water*
- *High level of water*
- *Many floating objects*

## Snow Fire Scenario:

- *Fast Spreading fire*
- *Dark/black smoke*
- *Mountainous*

# World Building



## Urban Flood Scenario:

- *Brown shade of water*
- *Low level of water*
- *Sparse floating objects*

## Grassland Scenario:

- *Small region of fire*
- *No trees*
- *Mountainous*

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# Unmanned Aerial Vehicles for NDM

**Unmanned Aerial Vehicles (UAVs)** are crucial in **Natural Disaster Management** for their ability to quickly access and survey affected areas, providing real-time data for rescue and recovery operations.

Their efficiency in mapping, delivering supplies, and monitoring hazards enhances response effectiveness.

By taking those in account, we use **AirSim**, a plug-in for **Autonomous Vehicles** simulation in **Unreal Engine 5**.

# AirSim Plug-in

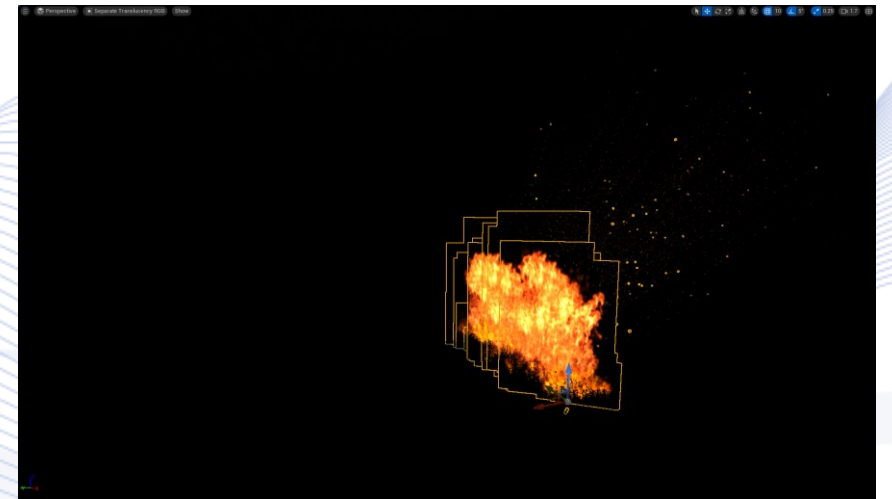
**AirSim** is a plug-in developed in C++ for **UAV** simulation in **Unreal Engine** while also having a **Python API**. It supports a wide range of cameras (**RGB, LiDAR, Depth, etc.**).

There are also custom cameras, e.g., **Segmentation** camera, which is the main tools for creating the datasets. **Segmentation** camera work by determining which object in the scene is projected in which pixel to create the mask.

# AirSim Plug-in

One of the main novelties of the work is the creation of the **Particle segmentation** camera. By default, particles do not appear in the segmentation camera, as only objects with volume are considered.

To create the **Particle segmentation** camera, a snapshot of the G-Buffer (a screen space representation of the geometry and material information, generated in render pass to create the final scene), is taken where only geometry and translucency is computed and by isolating the translucency elements we have the mask for the fire.

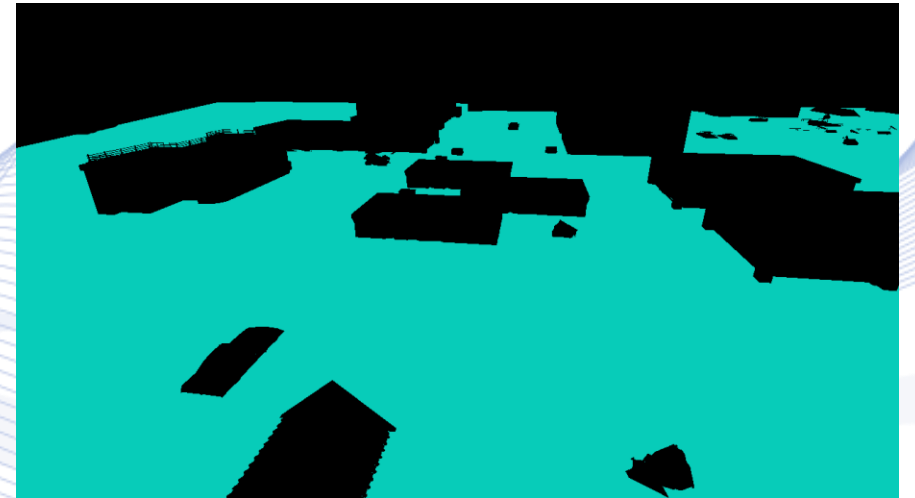


*Translucency buffer visualization*

# AirSim Plug-in

For the **Flood** scenario the same issue is present, because water is also transparent, it does not register in the segmentation camera of **AirSim**. The simplest way to get a mask of the water is to add a plane below the water and use this as the water mask.

**AirSim** also offers augmentations (weather effects, noise, etc.) enabling even more variations in the final images.



*Mask of flooded urban environment*

# Mission Planning

After forming the final version of the scene, by leveraging the **Python API of AirSim**, we set a path for the drone to fly covering the area from various angles and points of view.

The 2 main ways to fly the drone is either by giving it specific (**pitch, yaw, roll, throttle**) or by set custom **Splines paths** for the drone to follow.

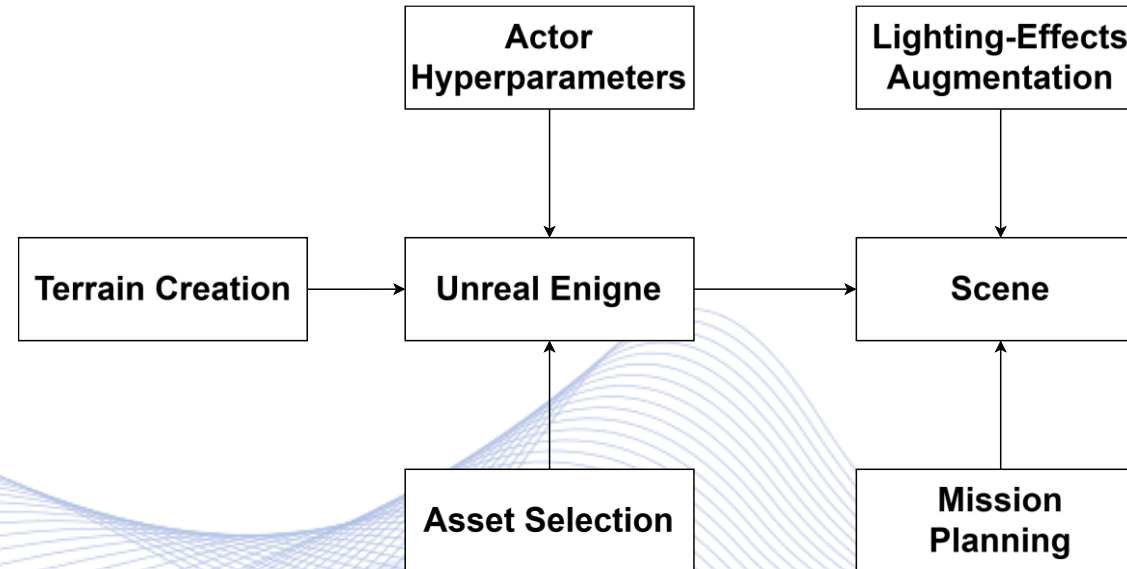
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# Simulation Pipeline

The default pipeline is as follows:

- Terrain creation
- Set the actors with desired assets
- Set the hyperparameters to control the disaster simulation
- Procedurally generate the actors in the scene
- Set the drone fly path



# Simulation Pipeline

After letting the simulation evolve, we have the paired **RGB – Mask** images.

By utilizing this pipeline, we can use the same settings for many iterations, changing just one or some of the setting to result in different images e.g., changing just the directional lighting (Position, intensity, color etc.) of the scene and keeping everything else the same (Terrain, assets, etc.).



*Soft shadows / Low temperature light*



*Sharper shadows / High temperature light*



# Synthetic Image Dataset for NDM

We created 2 different datasets covering :

- **Wildfires**
- **Floods**

Each of the datasets cover a wide variety of scenes. For the **Wildfires** dataset scenes range from **valleys to mountains, close to water bodies or not, with dense or sparse vegetation, different types of vegetation, one or more fires, small or large.**

The final version consist of around **2.500** subsampled frames from the **UAV** videos and all the scenes used provide about an equal number of frames.

# Synthetic Image Dataset for NDM

The **Flood dataset** also consist of around **2.500** images from a variety of **urban environments** and some **flooded rivers**. The main variations in the Flood dataset are not the different scenery as much as the following:

- Color of the water
- Level of the Water
- Objects in the water
- Lighting

# Synthetic Image Dataset for NDM

An import task for the **Wildfires** dataset is the pre-processing of the mask. As it was stated above the masks are pixel-accurate and that does not correlate with the masks of the real-world datasets



*Scene of the river scenario*



*Mask of the RGB scene*



*Refined mask of the RGB scene*

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# DNN Training

**Deep Neural Network (DNN)** require large amounts of data to effectively train them. In the field of **Natural Disaster Management (NDM)** where, despite the unwanted rise in the frequency in which they occur, images remain scarce even more so from a **UAV's** point of view.

Synthetic data can be used to cover for the missing real-world data, and by utilizing this pipeline, with minimum logistical effort.

# DNN Augmentation

The **Synthetic Wildfires** and **Synthetic Flood** datasets can be used to augment the real-world data even though the visual differences between the two.

We conduct a series of experiments training **DDNs** to segment real-world image, when it has been trained on either only synthetic or a mixture of synthetic and real-world images.

The results following are about the **Synthetic Wildfires** dataset.

# PIDNet and Datasets

For the experiments we use **PIDNet**, a real time state-of-the-art semantic segmentation network. As for the real-world image we use the **FLAME** dataset and the **Corsican** dataset.

- **FLAME** dataset consists of **2002** frames of a video captured from a **UAV** in a snow-covered forest for **fire segmentation**.
- **Corsican** dataset consists of **1122** images with some being frames from videos and covering a variety of scenes and fires.

# Results

## FLAME dataset split:

- First 1500 frames train
- Last 502 frames validation

## Corsican dataset split:

- Random images used as train
- Video frames used as validation

Train Set	MIoU FLAME Val	Train Set	MIoU Corsican Val
FLAME	91,66%	Corsican	95,77%
Synthetic only	56,78%	Synthetic only	63,46%
Synth + 1% F	67,88%	Synth + 1% C	86,64%
Synth + 2% F	69,36%	Synth + 2% C	90,07%
Synth + 5% F	70,49%	Synth + 5% C	92,69%
Synth + 10% F	69,29%	Synth + 10% C	91,56%
Synth + 25% F	75,24%	Synth + 25% C	94,40%
Synth + 50% F	89,94%	Synth + 50% C	95,54%
Synth + 75% F	91,56%	Synth + 75% C	95,69%



# Conclusion

To conclude, the key aspect of this work is the pipeline for the efficient creation of annotated synthetic image datasets. By utilizing the advanced capabilities of Unreal Engine 5, together with industry leading applications such as Maya or World Machine and the UAV plug-in AirSim, simulations of forest fires and floods became accessible and creation of valuable synthetic images regarding DNN training is achieved with minimum logistical costs.

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# Q & A

Thank you very much for your time!

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