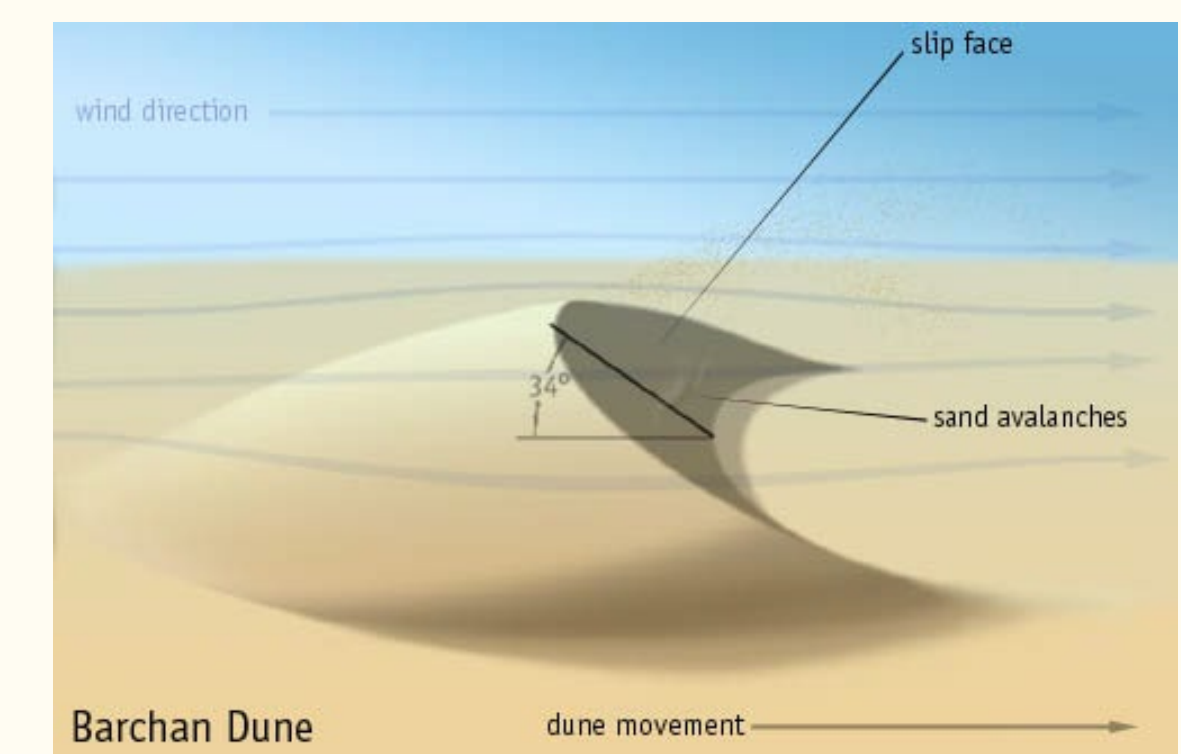
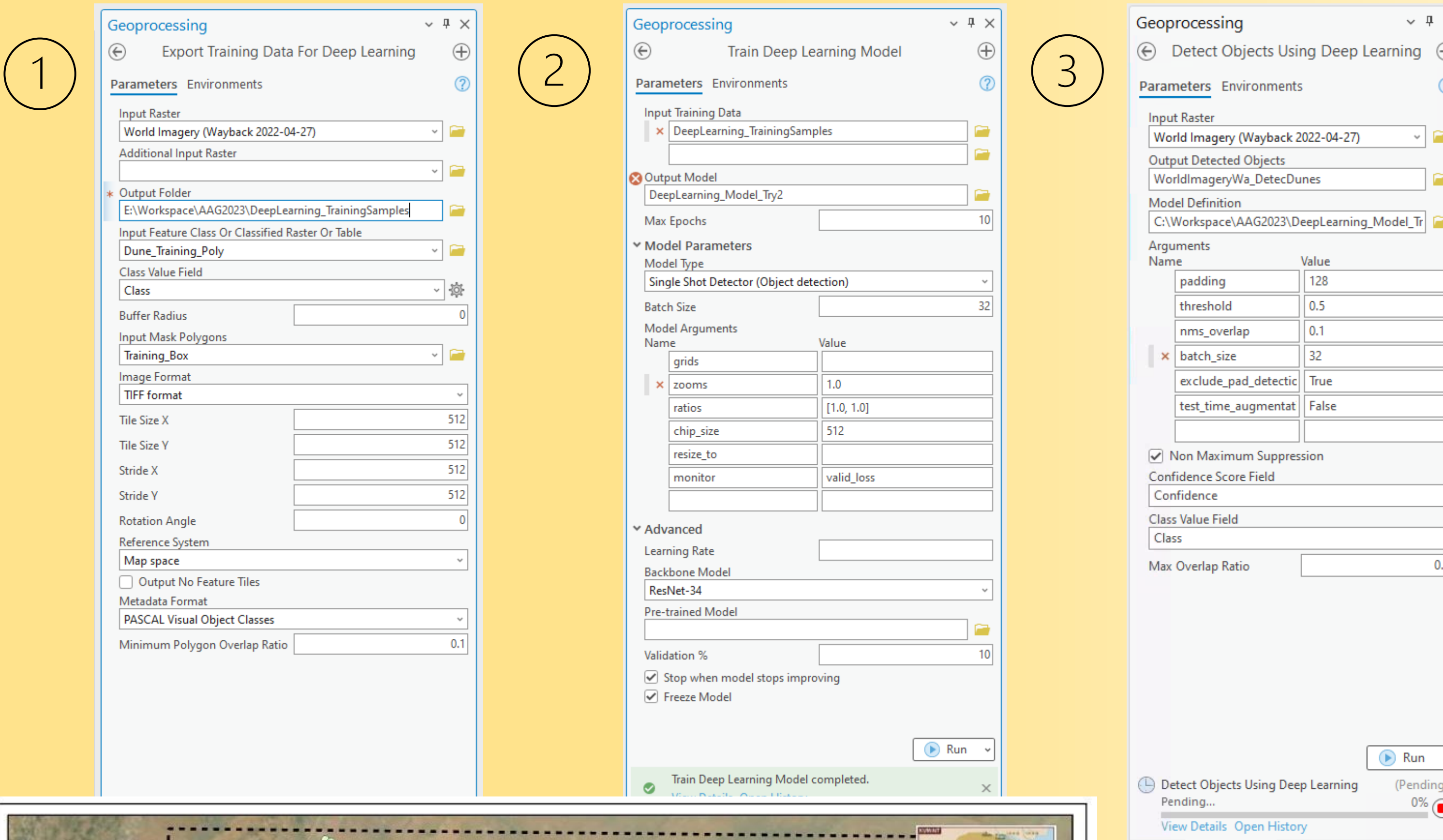




# Identification of Barchan Dune Locations from Satellite Imagery Using Deep Learning Methods in Kuwait

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ArcGIS Pro Settings for this Analysis



## Background

Deep Learning methods are now available that allow the identification of features within Satellite Imagery based on well-defined sets of training chips or samples. With the advent of Cloud storage of satellite data with pixel sizes of 10 meters or less, we now have multi-year and, in some cases, decadal time series of Satellite imagery available for analysis. In the recent past (< 10 years ago), it would take months to gather and prepare imagery for use before we could begin the analysis process for change detection. Deep Learning tools and modern image analysis methods are now available and integrated into Commercial software, making them available for use by the non-technical community.

## Study Goals

In this analysis ArcGIS Pro's Imagery Extension and Deep Learning modules are used to identify barchan dune locations within the country of Kuwait and identify their position and direction of movement. Initial assessments based on data from 2019-2022 indicate the dunes in northcentral Kuwait are migrating southeast (155 degrees) at the rate of approximately 14 meters per year. In Kuwait, knowledge of these rates and direction of movement are an important consideration when siting infrastructure since wind-blown sand can quickly overrun roads, utilities, and buildings if sand removal maintenance (analogous to snow removal) is not scheduled and planned for.

## Processing Methodology



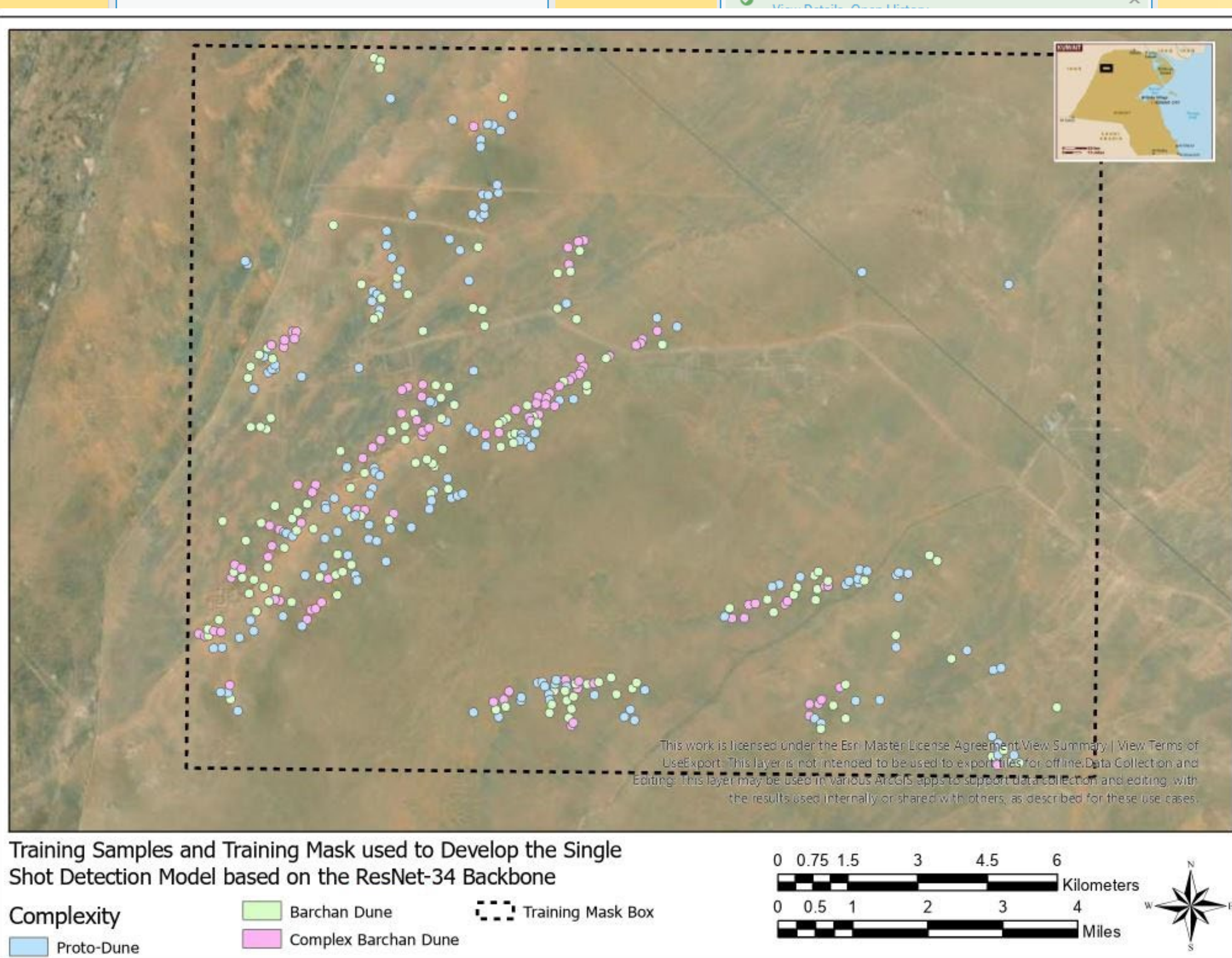
Step	Description
1	Create training samples in the <b>Label Objects for Deep Learning</b> pane, and use the <b>Export Training Data For Deep Learning</b> tool to convert the samples into deep learning training data.  Note: The Export Training Data For Deep Learning tool is also supported with the Spatial Analyst extension.
2	Use the <b>Train Deep Learning Model</b> tool to train a model using PyTorch, or train the model outside of ArcGIS Pro using a supported third-party deep learning framework.
3	Use the trained model to run the <b>Detect Objects Using Deep Learning</b> tool, the <b>Classify Pixels Using Deep Learning</b> tool, or the <b>Classify Objects Using Deep Learning</b> tool to generate an output.  Review and validate results using the <b>attributes</b> pane, and compute accuracy using the <b>Compute Accuracy For Object Detection</b> tool.

## Deep Learning Libraries Installers for ArcGIS



ArcGIS Pro, Server and the ArcGIS API for Python all include tools to use AI and Deep Learning to solve geospatial problems, such as feature extraction, pixel classification, and feature categorization. This installer includes a broad collection of components, such as PyTorch, TensorFlow, Fast.ai and scikit-learn, for performing deep learning and machine learning tasks, a total collection of 99 packages. These packages can be used with the **Deep Learning Training tools, interactive object detection**, by using the **arcgis.learn** module within the ArcGIS API for Python, and directly imported into your own scripts and tools. Most of the tools in this collection will work on any machine, but common deep learning workflows require a recent NVIDIA graphics processing unit (GPU), and problem sizes are bound by available GPU memory, see the **requirements section**.

Reference: <https://github.com/Esri/deep-learning-frameworks>



## Model Selection

Image analyses and image classification is traditional done utilizing pixel base classification methods. These methods took advantage of multiple bands of data (a.k.a., layers) that contain the measured spectral reflectance of a specific ground area (i.e., divided up into pixels) in three or more spectral bands (e.g., Red, Blue, Green, Near-infrared). Pixels may be classified into categories based on their reflectance values by comparing them to a unique signature for a known land cover type. At the simplest level, a Signature for a specific land cover type is a statistical description of the 'average' reflectance that a given land cover type has over all the measured bands. This concept remains the backbone of traditional image analysis and can be used to classify all pixels within an image into one or more classes.

A major limitation of traditional image analysis methods is they do not take advantage of the concept of 'Shape' when assigning pixels to a class. This limitation has been addressed with the development of object detection classifiers and models using Deep Learning concepts. These Convolutional Neural Networks take advantage of the spectral signature of each pixel, but also looks at the neighborhood around each pixel using the concepts of spatial correlation and edge detection. The output of these models are polygons (boundaries for an object) or points (representing the centroid of an object) for each object classified -rather than classified pixels as obtained with traditional image analysis methods.

In this study the default recommended settings provided by ESRI's ArcGIS Pro software were utilized when practical. The values used for the Training Sample Export, Model Training, and Classification steps are shown in the **'ArcGIS Pro Settings for this Analysis'** section of this poster.

The model used was **Single Shot Detection** with a maximum Epoch of 10 and Batch size of 32. The Backbone model selected was ResNet-32. These were selected to minimize processing time while achieving an object detection accuracy ( $\geq 80\%$ ). The Single Shot Detection method (ESRI Default) is designed to detect objects in images using a single deep neural network. Advantages of this method include (Liu et al. 2016):

- SSD eliminates proposal generation and subsequent pixel or feature resampling stages and encapsulates all computation in a single network.
- Easy to train and straightforward to integrate into systems that require a detection component.
- SSD has competitive accuracy to methods that utilize an additional object proposal step, and provides a faster unified framework for training and inferring.

**ResNet**, which stands for Residual Network, was used as the backbone model for this analysis. It is an innovative neural network available with several levels of complexity, represented by the number of layers used in building the model (He et al. 2016). Common levels include 16, 32, 50, and 101. When using ResNet the classifier can be run from 1 to many times until the desired accuracy is obtained or the maximum number of epochs hit. Previous studies have found accuracy does not improve significantly after 10 epochs for most objects in satellite imagery and that a layer depth of 32 achieves an acceptable accuracy rate while minimizing computational overhead (Melkozerov 2021).

## Barchan Dunes Training Samples

Training Deep learning models requires small sub-images, called image chips, that contain the feature of interest. These Chips are extracted from an image during the Training process based on classified polygon footprints (i.e., Training Samples). The output is a metadata folder and a folder of image chips showing the feature of interest. These are then used as input to Train and Build the Deep Learning Model.

The barchan dunes that were collected fell into three general sizes, analogs to stages of development: (1) proto-dunes without well defined horns (> 20 m in width), (2) developed barchan (> 40 m), and (3) large complex barchan (> 120 to 140 m). Complex barchans often had visible streamer on one horn that tended to feed into a second downwind barchan.



## Barchan Dunes – What are they?

A barchan or barkhan dune is a crescent-shaped dune first identified in Turkestan and other inland desert regions. Barchans face the wind, appearing convex and are produced by wind action predominantly from one direction. They are a common landform in sandy deserts and are arc-shaped, markedly asymmetrical in cross section, with a gentle slope facing toward the wind, comprising well-sorted sand. To develop they require a flat landscape, dominate winds from one direction, and limited sand supply that is blowing over a hard substrat.

Barchan's develop two "horns" that face downwind, with the steeper slope known as the slip face facing downwind and at the angle of repose of the sand in question, approximately 30–35 degrees for medium-fine dry sand. The upwind side is packed by the wind, and stands at about 15 degrees. Barchans may reach 9–30 m (30–98 ft) high and as wide as 370 m wide at the base (measured perpendicular to the wind direction).

In Kuwait the dune field receive a continues influx of aeolian sediment from Iraq that flows over the relatively flat caliche pavement substrate that forms most of the desert floor. The region has prevailing Westerly-Northwesterly winds, and generally flat topography that drops over 80 km from an average elevation of 150 m at the northwest border of Kuwait and Iraq to sea level at the coast near Kuwait City (< 0.2% slope).

In northwest Kuwait the Barchan dunes are migrating downwind and down slope to the southeast. Mean sediment size for the barchan dunes are characterized by a unimodal distribution, with an average grain size of 0.23 mm (Al-Awadhi and Misak 2000; Al-Dousari and Al-Hazza 2013). Bedload transport of sand and saltation is observed in the dune field whenever wind speeds exceeded 5.5 m/s under dry conditions (Al-Awadhi et al. 2000). Based on data for WMO Station Mitribah, from April 25, 2019 to August 28, 2020, this equated to 84 days (23%) of the year.

## Error Assessment

To prepare training data for this model 381 barchan dunes were identified using heads up digitizing methods within a 19.5 x 15.5 km training area (302 Km<sup>2</sup>) within the Al'Huwaitmlyah dune field (Al-Awadhi et al. 2000). Imagery used was from ESRI's World Imagery (Wayback 2022-04-27) data set. This site was visited and ground control collected between May 2020 and December 2020.

From these samples 35,601 image chips were generated or about 91 images per training sample site. These chips were used to develop the Single Shot Detector (SSD) model that met the 80% accuracy requirement (training loss 2.95, validation loss 45.96, and average precision of 0.794). When applied using the Detect Objects for Deep Learning Command a set of polygons identifying 'potential barchan dune' locations were created (confidence range of 56% to 99.5%). On visual inspection it was determined that type (2) and (3) barchan dunes had been identified and these had confidence values > 92%. A few false hits were observed, generally located at linear sand piles that had developed down-wind horns located alongside paved roads; however, these features are easily identified and removed.

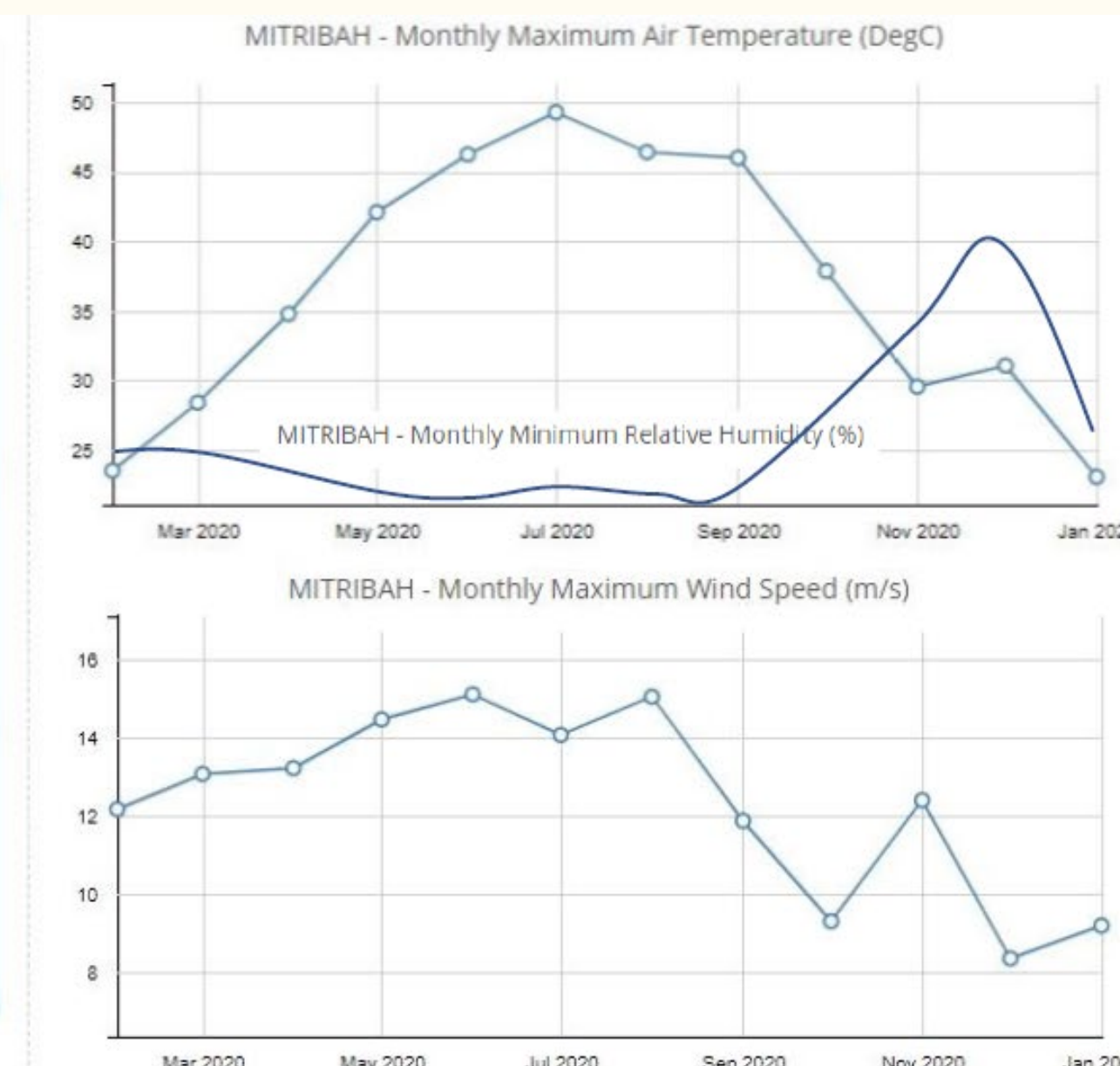
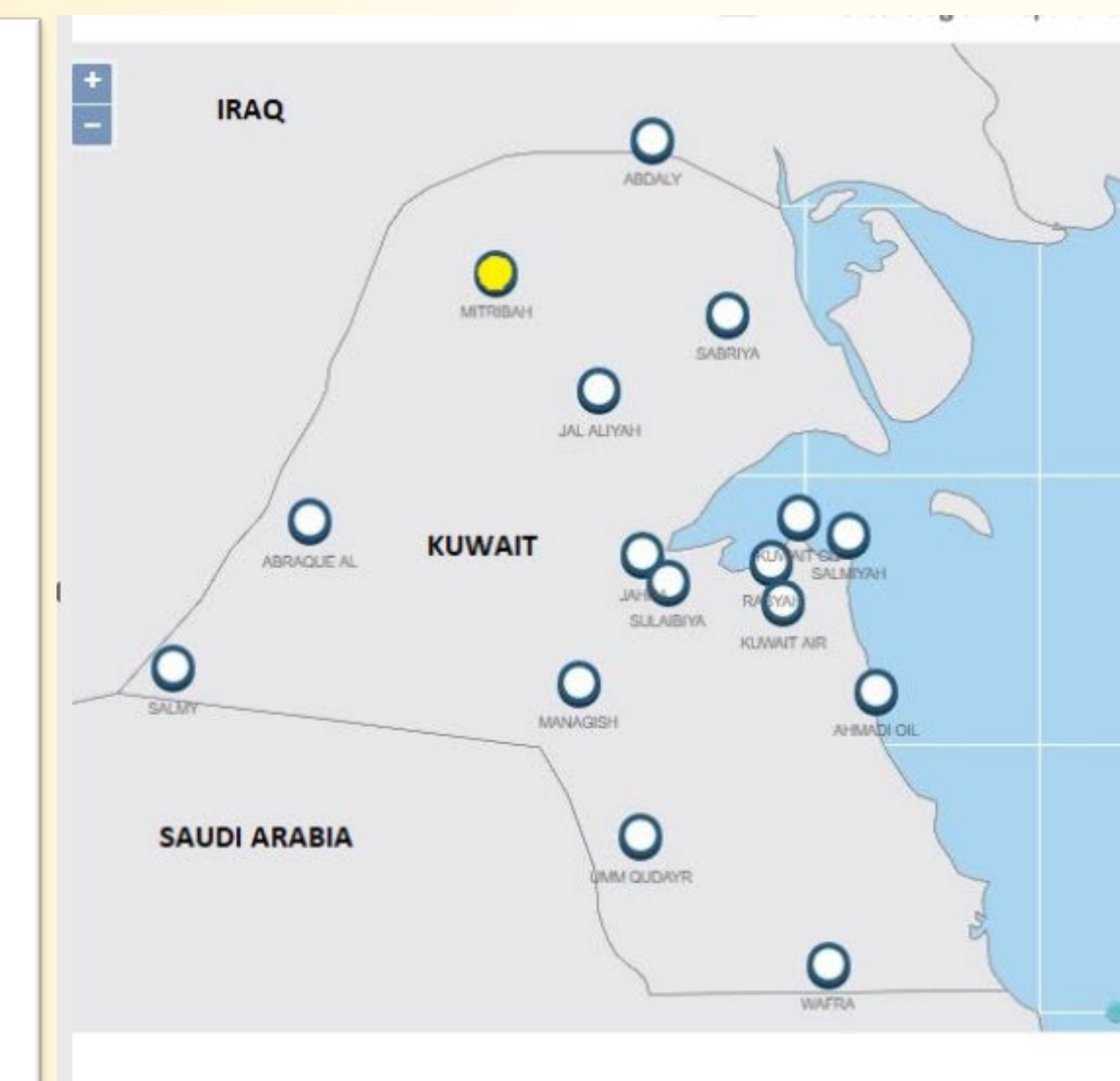
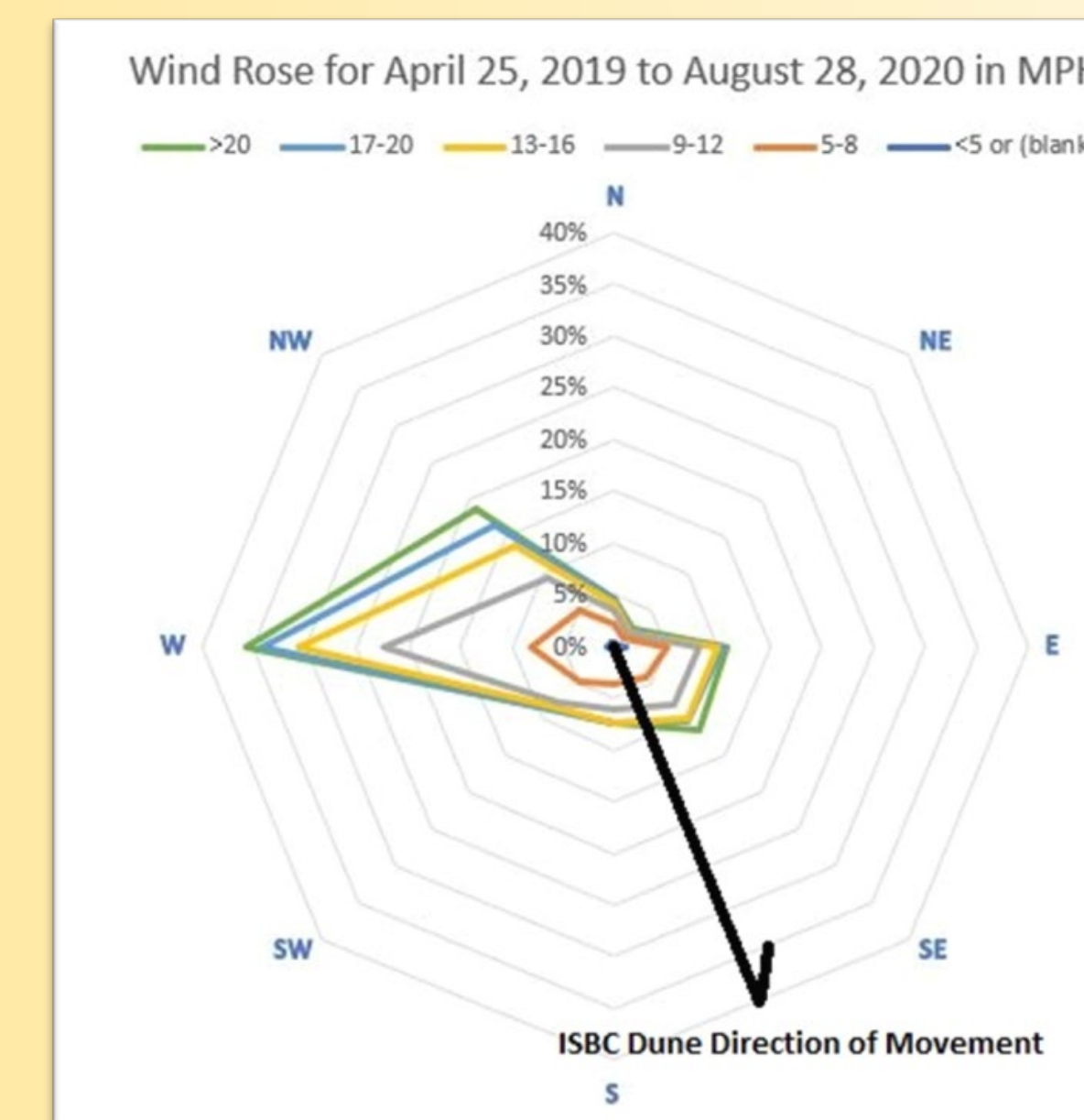
During **post-processing** polygons with confidence values > 92% were retained and were dissolved into polygons and the mean confidence interval calculated (generally increased to  $\geq 95\%$ ). These polygons were buffered by 10 meters (approximate 1/3 the box size) and boundaries dissolved. The resulting polygons now represented the general extent of the dune. These dune polygons were intersected with the training samples to generate an error assessment. In this analysis > 95% of type (2) and (3) barchan dunes used in training were successfully identified by the model.

## Results & Conclusions

The time required to conduct a single iteration of barchan dune identification using the deep learning workflow provided in ArcGIS Pro is measured in weeks for the first iteration and days for the second and Nth iteration. This is assuming the user meets the recommend software requirements of ArcGIS Pro 3 of > 100 Gbps internet connection, 32 Gb RAM, >= 4 core CPU, etc. on their machine. Since the scientific method requires multiple iterations to develop error estimates and configure the optimum parameters for the model it took two weeks to complete the 1<sup>st</sup> end-to-end assessment shown here for the training area. It would have been faster to collect the barchan dunes using heads-up digitizing methods. However, the model can now be run against multiple imagery datasets collected during different time periods. Future research will look at how the results from these object classification runs can be used to measure dune migration in the Kuwait over 2, 5 and 10 year periods. In addition, this type of model may be used in other arid regions of the world to build a better understanding of the spatial extent of barchan dune fields.

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\*Climate Statistics for WMO Station Mitribah. The May-October dry season is a period of low humidity and high temperatures with wind speeds high enough to initiate sediment motion.