

Predicting hydraulic head levels with machine learning

Brytne Okuhata
CEE696-007 (Fall 2019): Final Project
December 19, 2019

Introduction: Hydrologic Cycle

- Precipitation infiltrates as recharge
- Aquifer: lens-shaped fresh water body
- Dikes can withhold groundwater

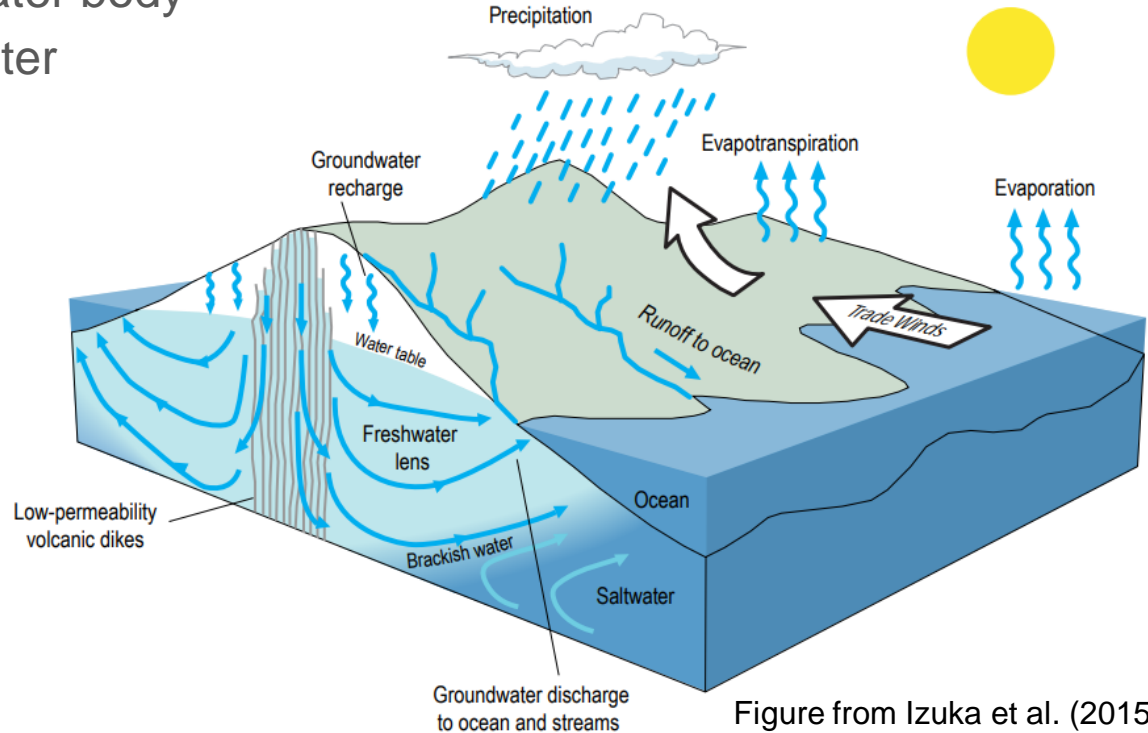


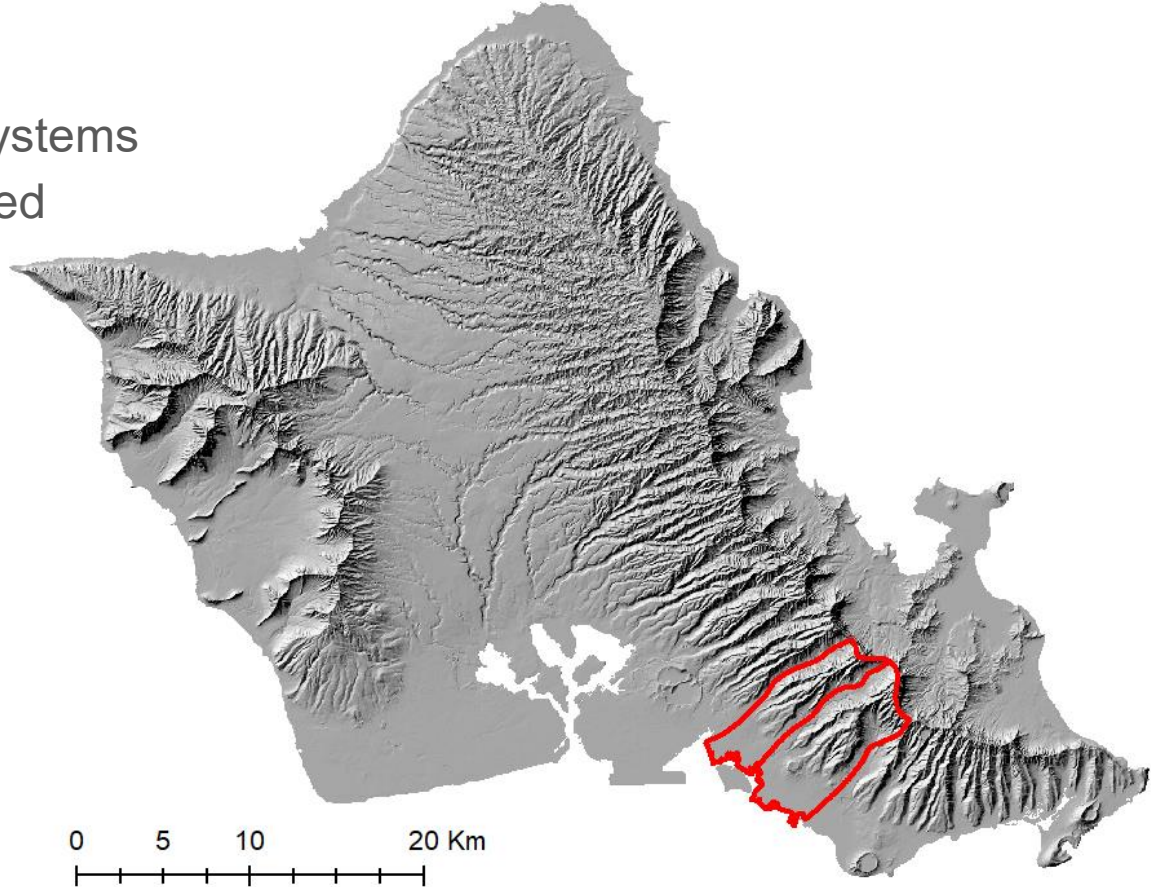
Figure from Izuka et al. (2015)

Motivation

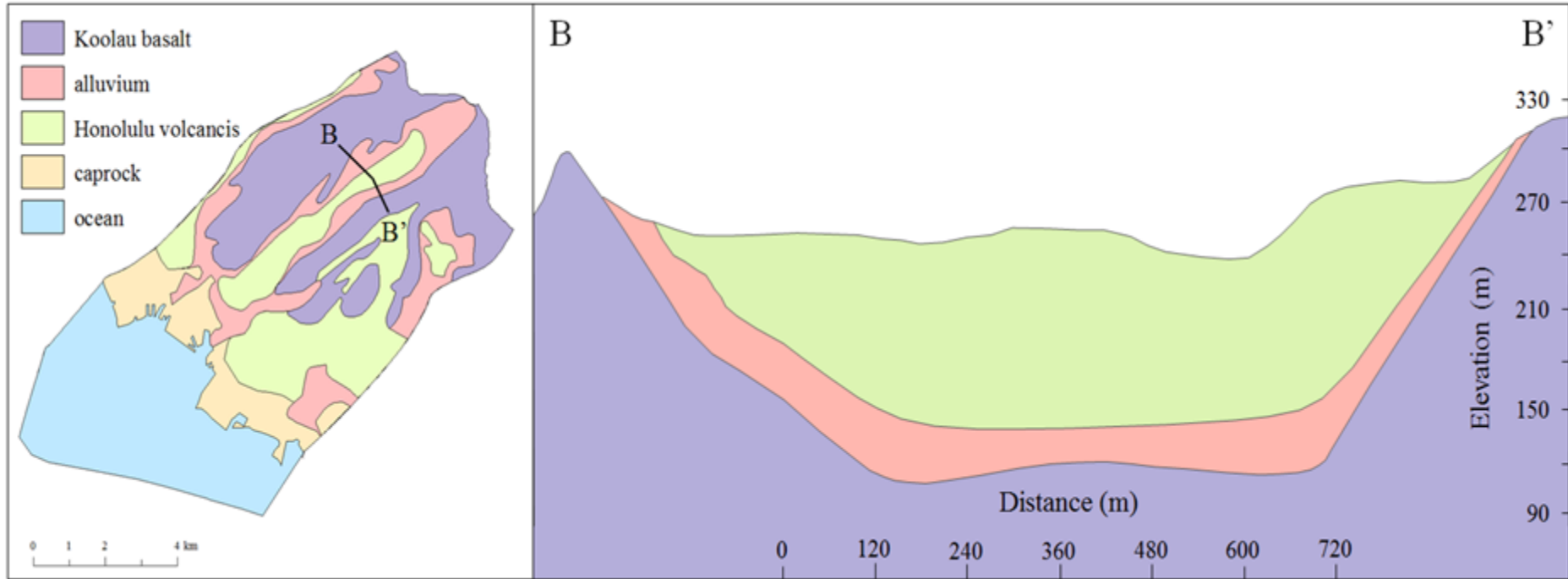
- O‘ahu has a large population which requires a large quantity of water
- Groundwater is primary source of Hawaii’s fresh water
- It’s important to know how much water is available for pumping
- Therefore, it’s important to understand how the hydrogeology controls groundwater flow and storage

Study Site

- Nu‘uanu and Kalihi aquifer systems
- Part of the Honolulu watershed



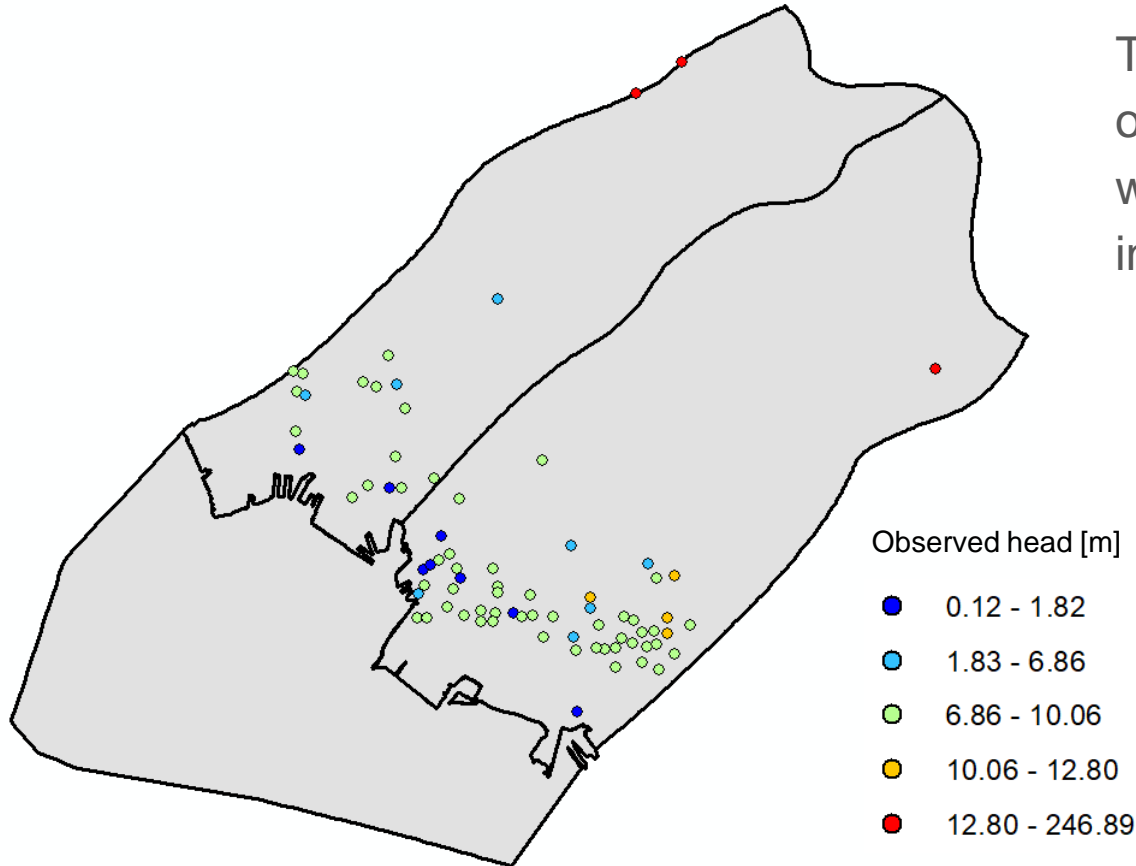
Complex Hydrogeology



Figures interpreted from Sherrod et al. (2007) and Wentworth (1941)

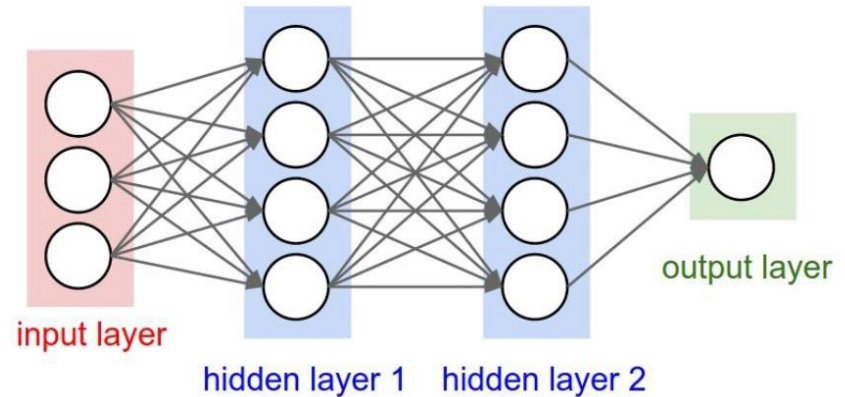
Limited Monitoring/Pumping Wells

There's a poor spatial distribution of monitoring and/or pumping wells, which reduces confidence in model calibration.



Methods Overview

- Develop simple 3D model in GMS using MODFLOW (<http://www.aquaveo.com>)
- Utilize FloPy (Bakker et al., 2019) to read model files using python
- Simulate different hydraulic conductivity scenarios to yield different synthetic hydraulic head results
- Use the scenario results to train a DNN model to predict hydraulic heads



Neural Network

(image credit: <http://cs231n.github.io/neural-networks-1/>)

Random hydraulic conductivity scenarios

```
result_array = []  
iterations = range(501)
```

Assign the number of scenarios you want to run

```
for i in iterations:
```

```
    mf_object = flopy.modflow.Modflow.load('Nuuanu_v2_take1.mfn', exe_name=exe_name, verbose=True,  
    check=True, forgive=False)  
    temp_hk = mf_object.lpf.hk.array
```

Initiate GMS MODFLOW file

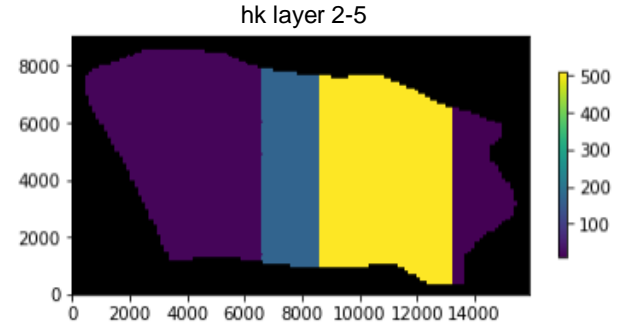
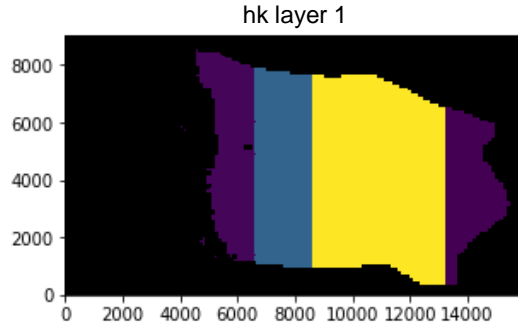
```
    # loop over every iteration and assign random values to each hk zone  
    hkz1 = random.randint(10,40); temp_hk[:, :, 0:50] = hkz1  
    hkz2 = random.randint(100,200); temp_hk[:, :, 50:65] = hkz2  
    hkz3 = random.randint(500,1000); temp_hk[:, :, 65:100] = hkz3  
    hkz4 = random.randint(1,10); temp_hk[:, :, 100:120] = hkz4
```

Randomly assign HK values

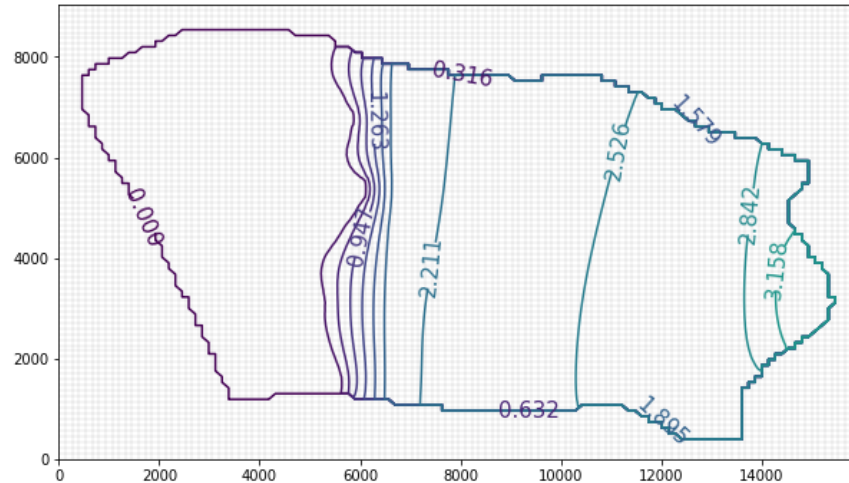
```
    # assign temp_hk to lpf.hk  
    mf_object.lpf.hk = temp_hk  
    mf_object.write_input()  
    success, buff = mf_object.run_model()  
    layer=2
```


Example Output

HK zone 1 = 15 m/d
HK zone 2 = 169 m/d
HK zone 3 = 509 m/d
HK zone 4 = 9 m/d



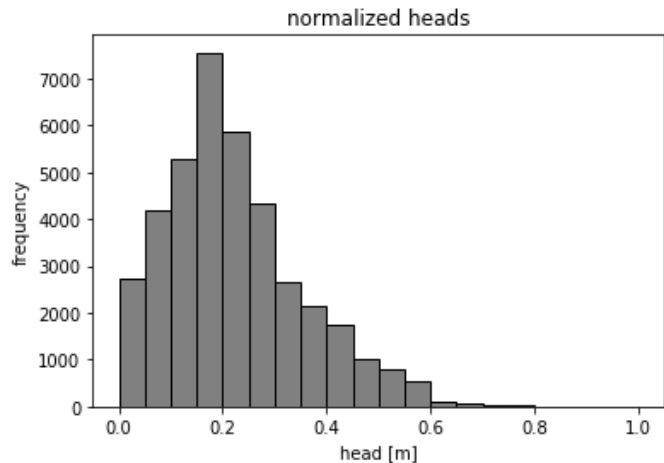
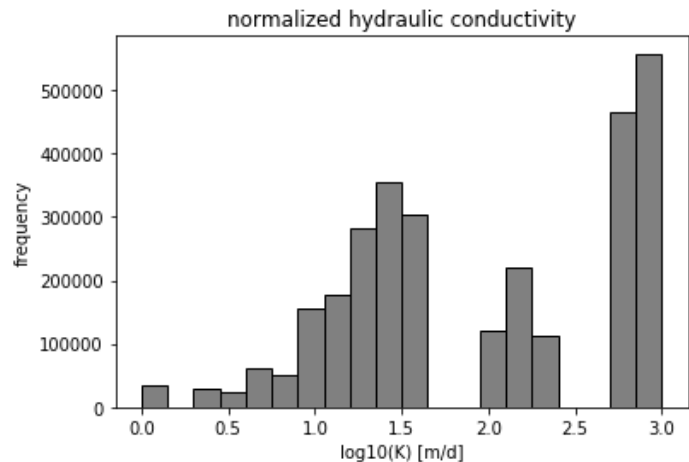
Resulting head contours [m]



Normalize the data

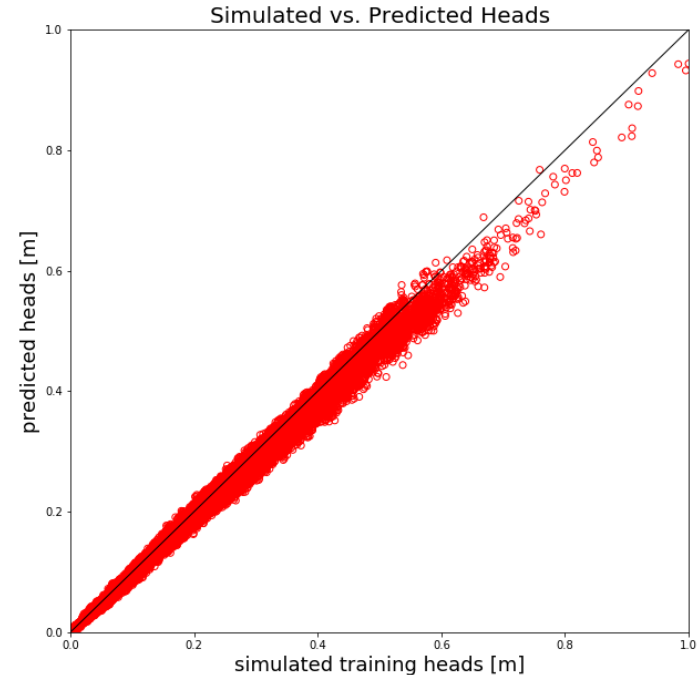
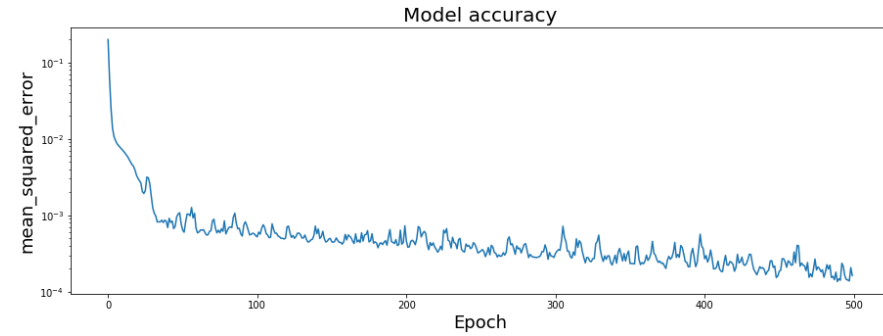
```
x_train = np.zeros((501, 5881)); y_train = np.zeros((501, 78))
for i in range(501):
    hk_training = np.loadtxt('hk_dist_%d.txt'%(i))
    head_training = np.loadtxt('sim_heads_dist_%d.txt'%(i))
    x_train[i,:] = hk_training; y_train[i,:] = head_training

x_train_log = np.log10(x_train)
y_train_min = y_train.min()
y_train_max = y_train.max()
y_train_norm = (y_train-y_train_min)/(y_train_max-y_train_min)
```



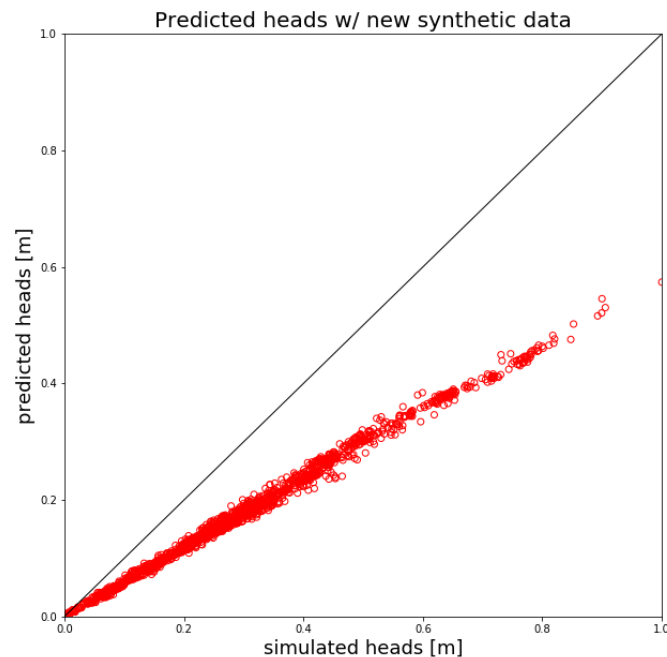
Training DNN Model

```
model = Sequential()  
model = tf.keras.Sequential()  
model.add(Dense(64, activation=relu, input_shape=(5881,)))  
model.add(Dense(64, activation=relu))  
model.add(Dense(64, activation=relu))  
model.add(Dense(64, activation=sigmoid))  
model.add(Dense(78))  
model.compile(optimizer='adam',  
              loss='mean_squared_error',  
              metrics=['mse'])  
.  
.  
history = model.fit(x_train_log, y_train_norm,  
                   epochs=500, validation_data=None,  
                   batch_size = 64)  
.  
.  
y_pred = model.predict(x_train_log)
```



Future Work

- Simulate a more complex hydrogeology within FloPy
- Calibrate the model with measured head levels rather than synthetic heads
- Apply the DNN model to new test data
- Extend to a CNN model



References

Bakker, M., Post, V., Langevin, C. D., Hughes, J. D., White, J. T., Leaf, A. T., Paulinski, S. R., Larsen, J. D., Toews, M. W., Morway, E. D., Bellino, J. C., Starn, J. J., and Fienen, M. N., 2019, FloPy v3.3.0: U.S. Geological Survey Software Release, 14 December 2019, <http://dx.doi.org/10.5066/F7BK19FH>

Gingerich, S.B. and Oki, D.S., 2000. Groundwater in Hawaii. U.S. Geological Survey Fact Sheet. <https://pubs.usgs.gov/fs/2000/126/pdf/fs126-00.pdf>.

Izuka, S.K., Engott, J.A., Bassiouni, M., Johnson, A.G., Miller, L.D., Rotzoll, K., Mair, A., 2015. Volcanic Aquifers of Hawaii - Hydrogeology, Water Budgets, and Conceptual Models. U.S. Geological Survey Scientific Investigations Report 2015-5164. 158 p.

Sherrod, D.R., Sinton, J.M., Watkins, S.E., Brunt, K.M., 2007. Geologic Map of the State of Hawaii: U.S. Geological Survey Open-File Report 2007-1089, 83 p., 8 plates, scales 1:100,000 and 1:250,000, with GIS database.

Wentworth, C.K., 1941. Geology and ground-water resources of the Nuuanu-Pauoa District. Honolulu Board of Water Supply, 218 p.