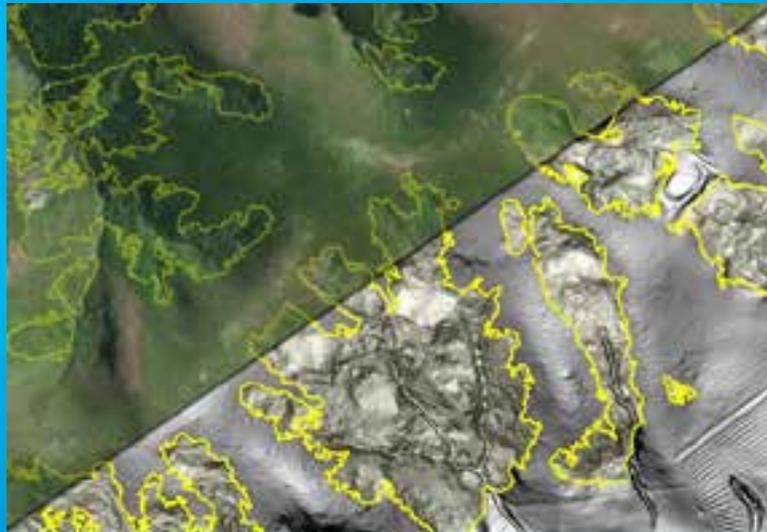


UC 1226, Automated Landslide Detection

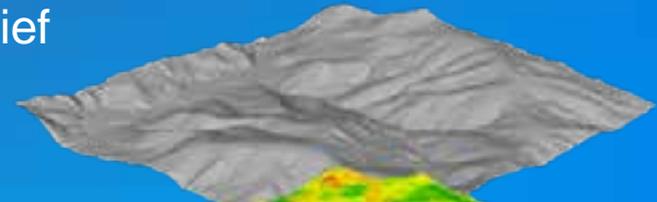
Josh McLaughlin
Geophysical Analytics, QSI



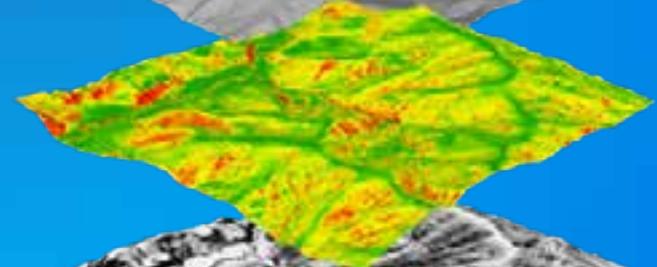
Aerial imagery (top left) and Quantum Spatial enhanced relief DEM (bottom right) with classified landslide areas

- **Comprehension of geologic processes is of great concern to many modern industries such as infrastructure planning, energy distribution, forestry management, and emergency response. Utilizing an automated approach, Quantum Spatial has developed an accurate and efficient methodology, which detects areas of failed terrain using high-resolution LiDAR data (15 pts/m²). The result is a robust, efficient, cost-effective dataset that indicates the presence of landslides, fault lines and other forms of failed terrain.**
- **LiDAR modeling reveals subtle surface features that are undetectable via aerial photographs or field observation, which leads to unparalleled richness in topographic models. Quantum Spatial LiDAR accuracies (RMSEz 3-5 cm) are second to none, providing the necessary foundation for assessing terrain attributes associated with landslides.**

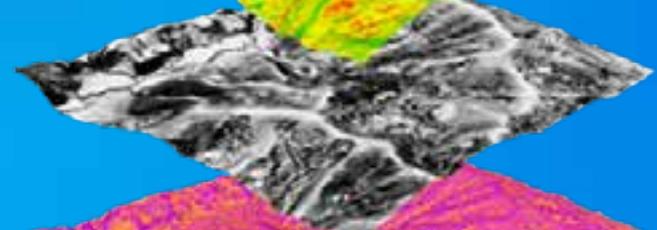
Shaded Relief



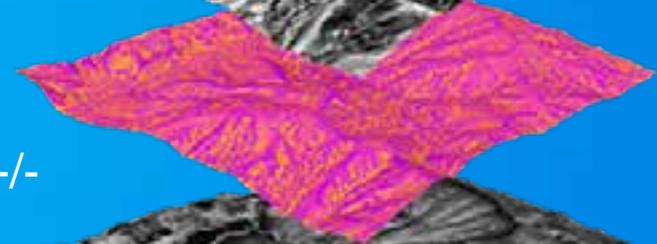
Slope



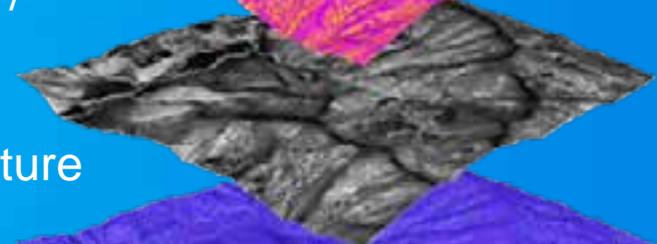
Roughness



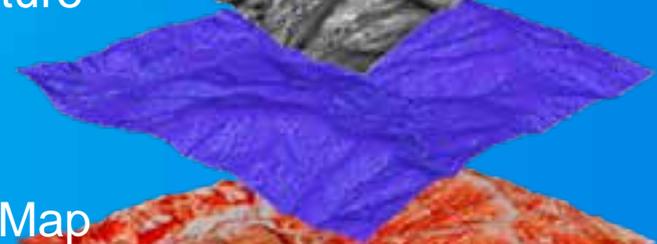
I-value



Openness +/-



Plan Curvature



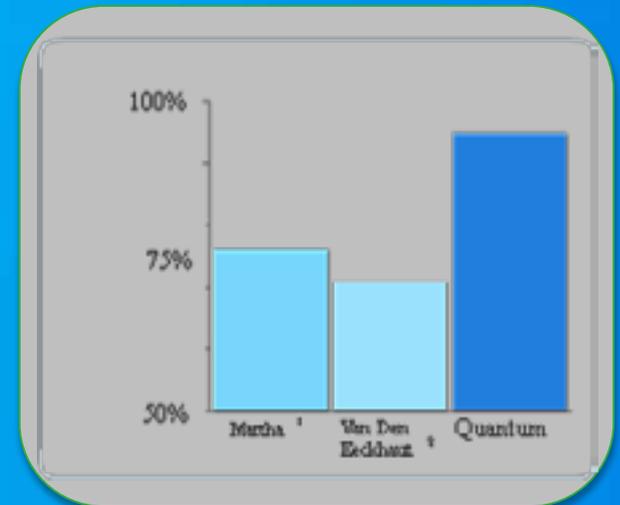
Red Image Map



Quantum Spatial achieved a 95% accuracy for landslide detection



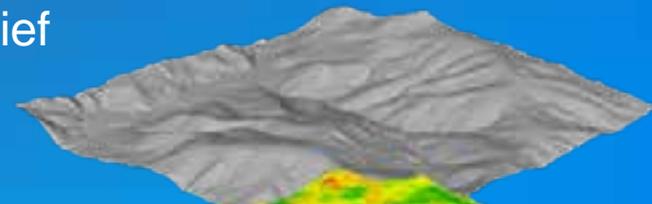
34	0.1726		
1	0.24756		
13	0.30845		
22	0.31021		
6	0.31854	Mean	1.732074211
35	0.31905	Standard Error	0.236954732
3	0.37420	Median	1.01773
4	0.39281	Mode	#N/A
2	0.42849	Standard Deviation	1.78927099
0	0.45063	Sample Variance	3.201490676
20	0.5145	Minimum	0.03156
39	0.53566	Maximum	9.66945
36	0.61741	Count	57
17	0.6674	Confidence Level (95.0%)	0.474757498
32	0.67104		
16	0.74108		
19	0.84023		
18	0.87136		
26	0.90898		
33	1.01386		



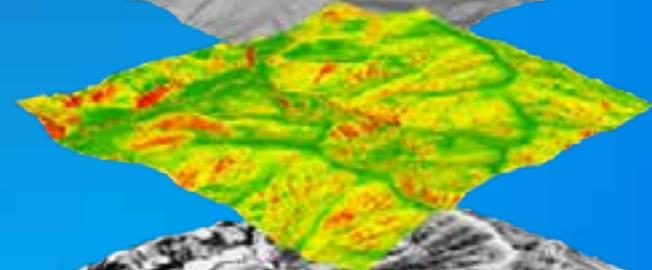
Quantum Spatial classification accuracy compared to results from two notable, published studies

- Landslide detection relies on a detailed bare-earth DEM derived from a LiDAR ground model. Ground-classified LiDAR points are first processed to create a variety of raster images which reveal different landform features unique to landslides and faults. These images are then used as inputs for a series of semi-automated classification steps. The various algorithms include
- a combination of iso-clustering, principal component analysis, and support vector machines, which result in an initial landslide classification.
- A step-wise procedure systematically pares the model, excluding non-landslide and non-fault areas from the analysis (e.g., cultivated fields, roads, lakes) that may appear in the initial processing steps.

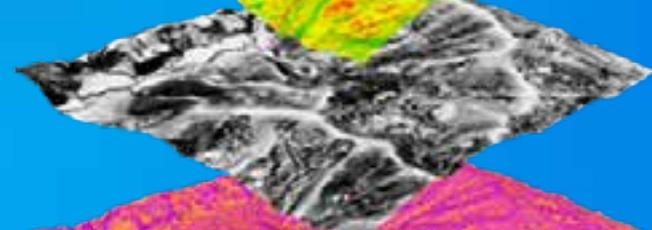
Shaded Relief



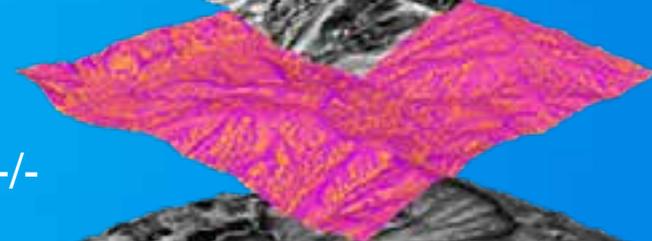
Slope



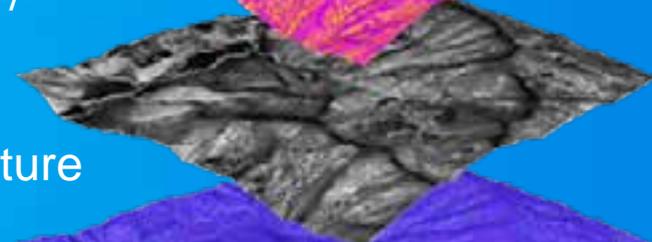
Roughness



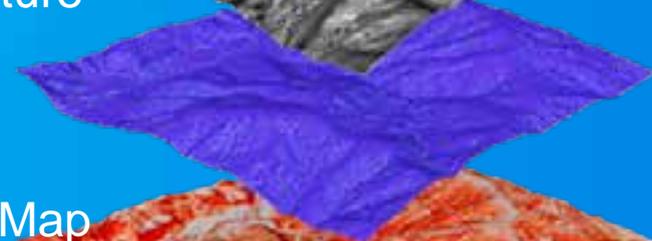
I-value



Openness +/-



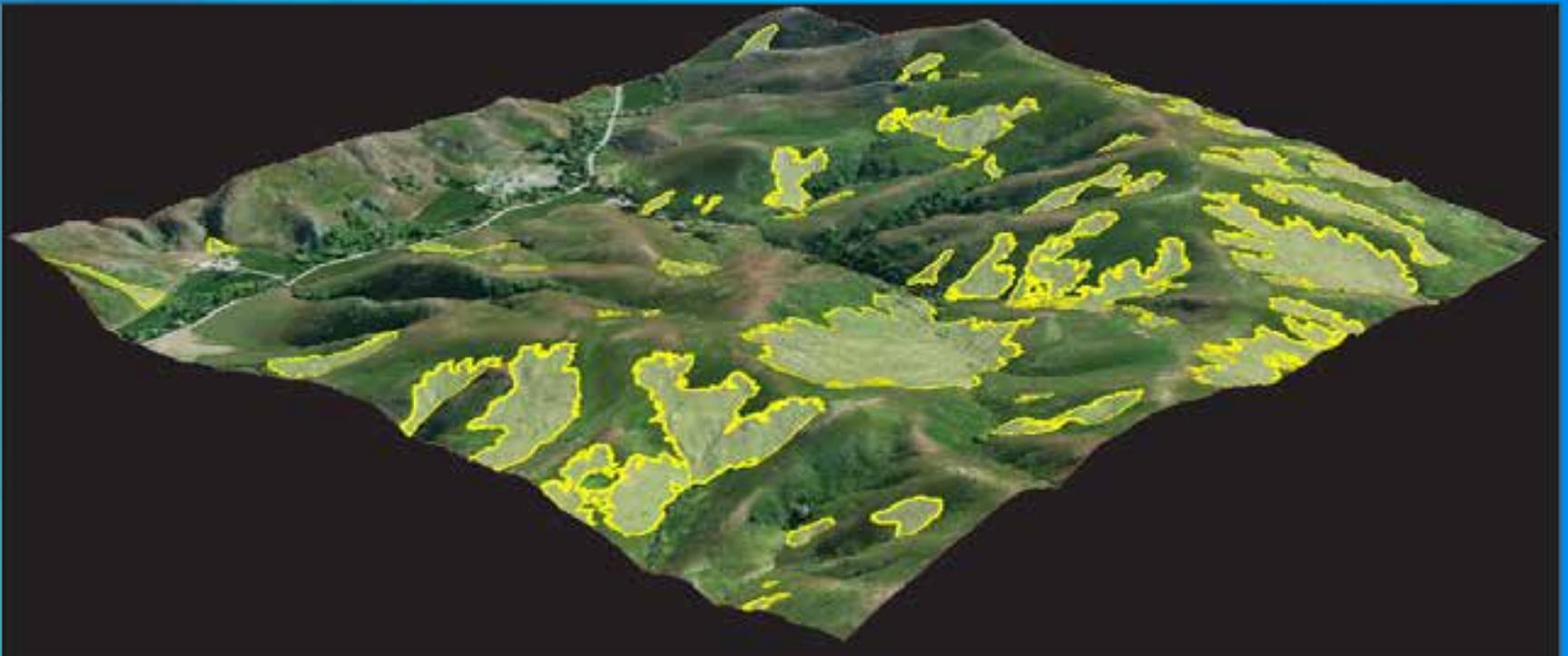
Plan Curvature



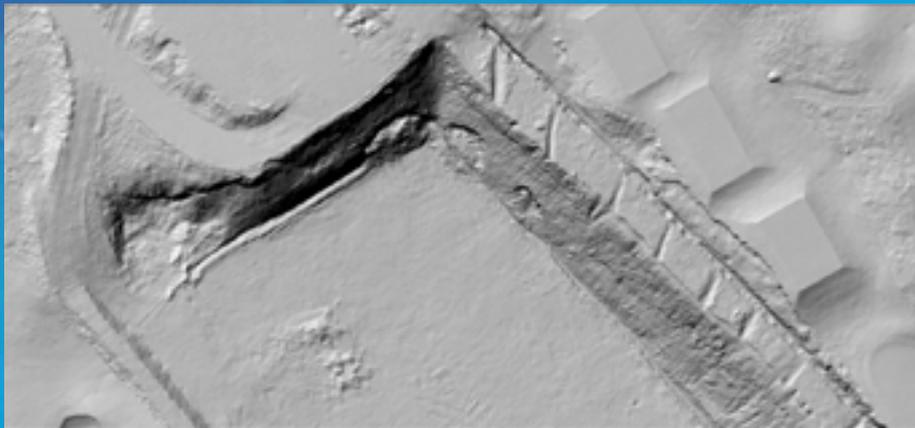
Red Image Map



- **Iso-Clustering** is used to separate the survey region into several distinct classes. This classification technique is an iterative optimization procedure that repeatedly assigns cluster centers, based on the multi-dimensional, topographic characteristics of each input raster image. After each classification step, the algorithm evaluates the results by measuring the minimum distances within each cluster. Each iteration of the procedure causes unique morphological clusters to migrate together.



- Once the automated detection is completed, manual editing is performed to eliminate false-positives and to refine the geometry of landslide delineations and fault lines.

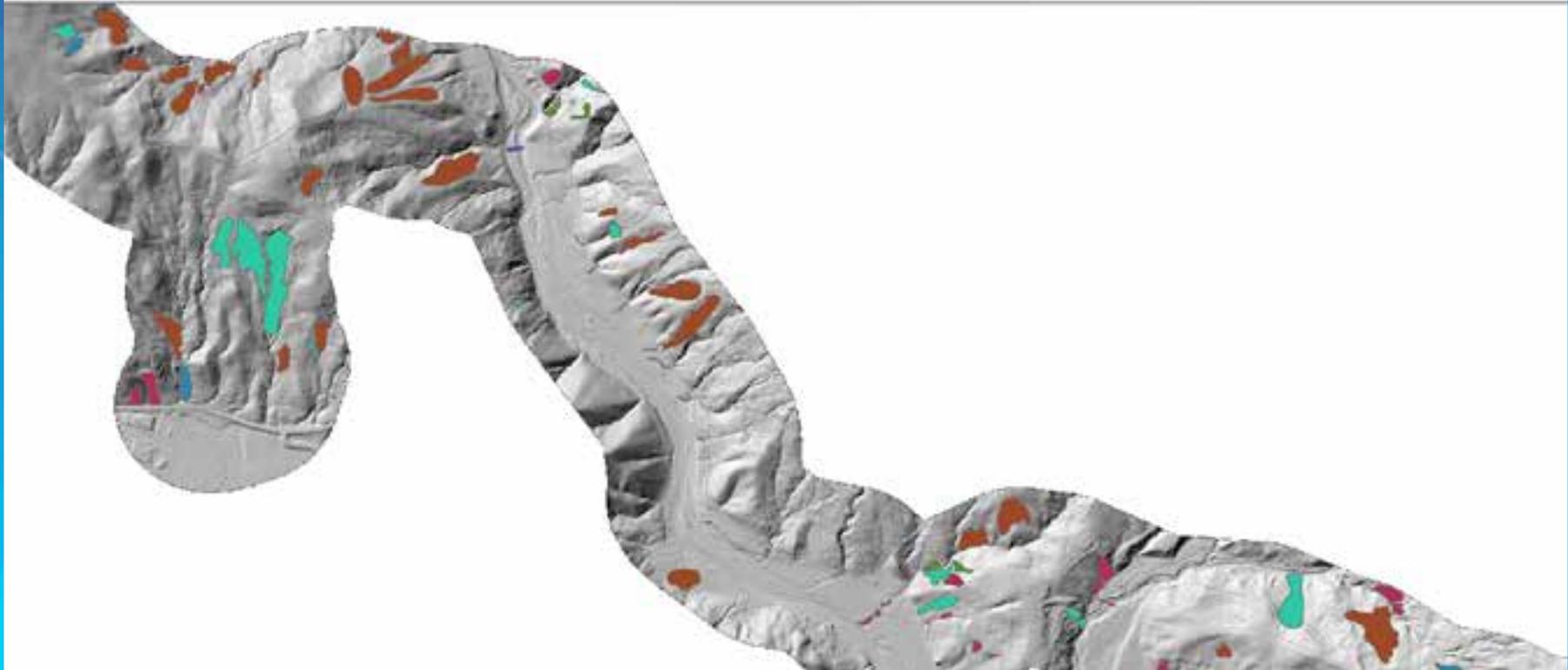


- Upon completing landslide delineation, the landslide areas are automatically assigned respective slope angle, aspect, mean annual precipitation, vegetation cover, and soil attributes.

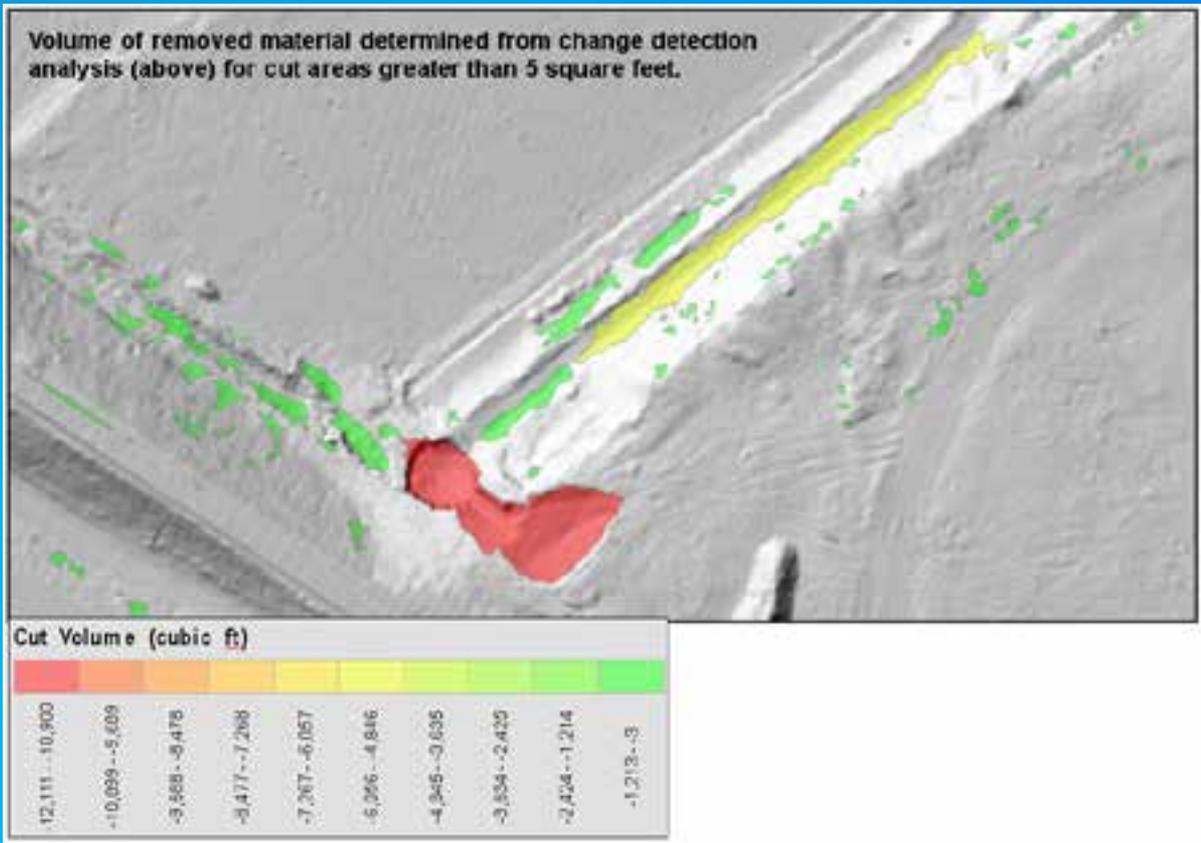
ID	Shape	OBJECTID	Soil Unit	Soil Type	As Frocp	Infilted	Soil Prof	Liq Lim	Plas Ind	BS' Bedrock	HorzdType
2	Polygon	2	Rock outcrop-Dubautia-HeidiHysc families complex	rock outcrop	40 to 65 inches	CL	0 - 4, unweathered bedrock / E - 11, very cobbly loam T1 -	25 - 30	5 - 10	C to 20 inches	slate
3	Polygon	4	Rock outcrop-Dubautia-HeidiHysc families complex	rock outcrop	40 to 65 inches	CL	0 - 5, unweathered bedrock / E - 11, very cobbly loam T1 -	25 - 30	5 - 10	C to 20 inches	slate
4	Polygon	5	Ocala-Hecker-Ody families association, deep	silty clay loam	55 to 75 inches	CH	0 - 3, silty clay loam, 3 - 40, silty clay, 40 - 60, granoly clay	25 - 60	5 - 35	60 to 64 inches	slate
5	Polygon	6	Ocala-Hecker-Ody families association, deep	silty clay loam	55 to 75 inches	CH	0 - 3, silty clay loam, 3 - 40, silty clay, 40 - 60, granoly clay	25 - 60	5 - 35	60 to 64 inches	earth flow
6	Polygon	7	Ocala-Hecker-Ody families association, deep	silty clay loam	55 to 75 inches	CH	0 - 3, silty clay loam, 3 - 40, silty clay, 40 - 60, granoly clay	25 - 60	5 - 35	60 to 64 inches	erosn
7	Polygon	8	Ocala-Hecker-Ody families association, deep	silty clay loam	55 to 75 inches	CH	0 - 3, silty clay loam, 3 - 40, silty clay, 40 - 60, granoly clay	25 - 60	5 - 35	60 to 64 inches	erosn
8	Polygon	9	Rock outcrop-Dubautia-HeidiHysc families complex	rock outcrop	40 to 65 inches	CL	0 - 4, unweathered bedrock / E - 11, very cobbly loam T1 -	25 - 30	5 - 10	C to 20 inches	earth flow
9	Polygon	11	Ocala-Hecker-Ody families association, deep	silty clay loam	55 to 75 inches	CH	0 - 3, silty clay loam, 3 - 40, silty clay, 40 - 60, granoly clay	25 - 60	5 - 35	60 to 64 inches	slate

8 out of 130 Selected

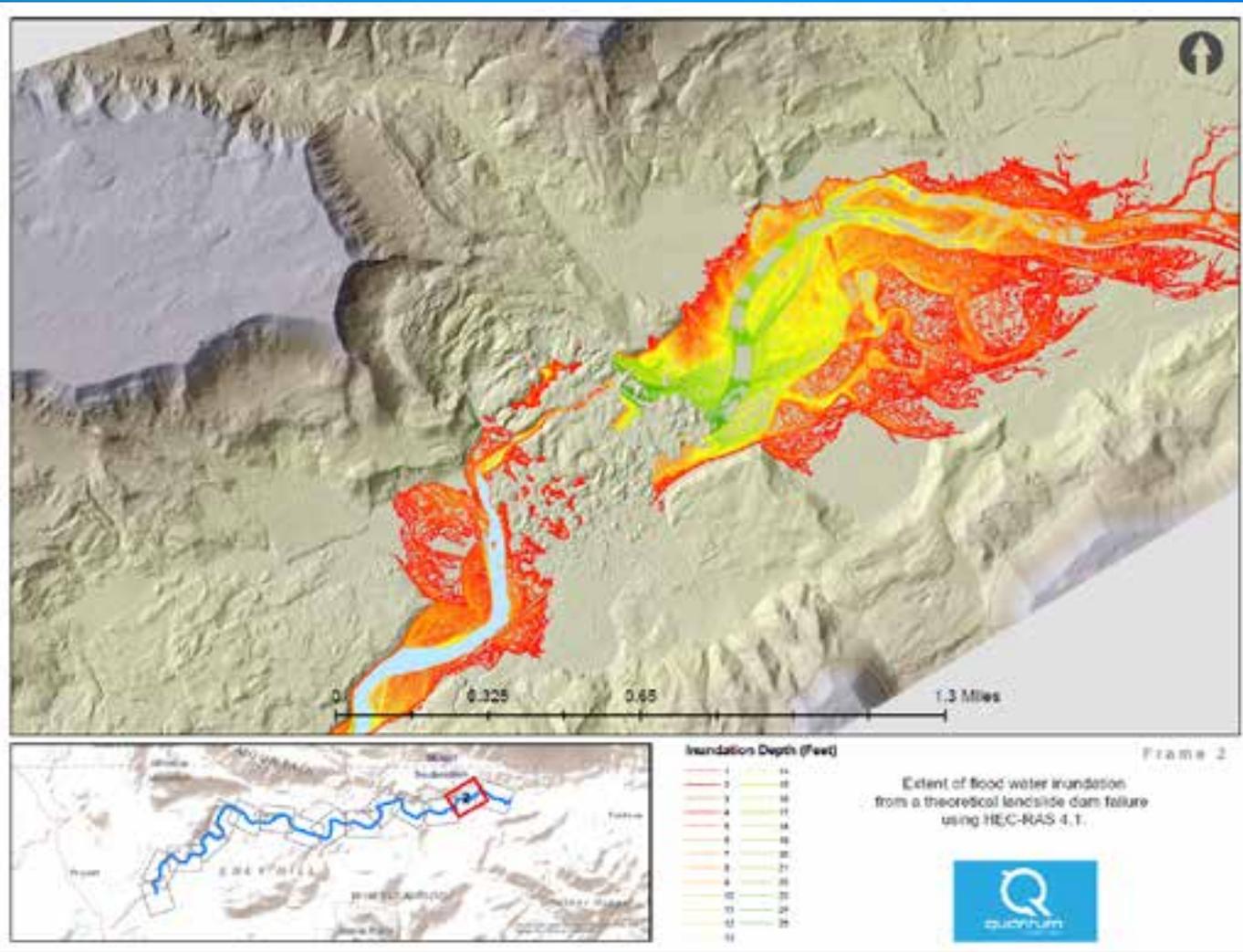
rnty_Terrain_Feature_polygons



Next, we hope to incorporate volume analytics to move us toward a predictive model.



And help mitigate risk management for these known hazards



And leverage our knowledge to discover insights yet to be realized

Josh McLaughlin
jmclaughlin@quantumspatial.com

