4D CHANGE DETECTION

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ABSTRACT

The purpose of this paper is to show how the utilization of Digital Surface Models (DSMs) in the change detection problem can mitigate analyst fatigue, enhance data fusion, perform cross modality change detection, and be used to model illumination & shadow effects. We register two DSMs and subtract them from each other to obtain residual height information (named a **Q-DSM)**. Implicitly there is a relationship between the Q-DSM and the original DSM; hence we can exploit this relationship to reduce fatigue for the analyst and minimize the search space for changes. Moreover, if the original Digital Surface Models are from disparate modalities then we can implicitly map 3D residual changes to 2D modality disparate imagery (e.g., Correlated DSM from Synthetic Aperture Radar & Electro-Optical Imagery). Finally, we can model illumination differences in 3-Space and project those changes into 2-Space such that if an image was collected with varying aspect angles then we can ascertain if there was true change or change attributed to shadow and illumination effects. Therefore, shadow-masked 2D and 3D change detection can be realized. Our end product can be viewed in 3D Visualization tools such as Harris InReality, Google Earth, and NASA Worldwind.

Keywords: Digital Surface Model, Cross Sensor Change Detection, Data Fusion, 3D Shadow

PROBLEM STATEMENT

The process of finding *relevant* changes from one scene to the next is called change detection. Normally, this is performed by an image analyst viewing image sets along with associated intelligence about the scenes in question. Image analysts are constantly inundated with static 2D imagery products; these products are usually overlaid with colors for cueing purposes. Over time, analysts become fatigued and important change from one scene to next may be missed. GIS-Data collection is becoming more and more ubiquitous. Thus, a large amount of collected data is underutilized. Trying to utilize the data through fusion and horizontal integration has become an important part of the Intelligence Community. Also, being able to create actionable information with Commercial GIS-related applications is desirable. Given the recent explosion of available imagery data, Digital Surface Models (DSM) and the increasing number of Areas-of-Interest throughout the world, the trend is towards rapid, automated and analyst aided change detection algorithms. Our purpose is to combine GIS data to help the analyst make a more informed decision. We begin by reviewing some of the current methodologies with respect to how the change detection problem is being solved. Afterward, we build a case to show how our contribution can make the analyst's job easier and more accurate.

CURRENT METHODOLOGY

Change Detection (CD) is the process of locating user desired changes between two 2D scenes. Currently a combination of sophisticated pixel correlation techniques in conjunction with human analysts are employed to find mission specific changes. The analyst identifies differences based on intelligence, usually human, that has been gathered to cue him/or her to the relevant *actionable* changes. Despite the best preprocessing and correlation algorithms, the analyst is often required to sift through the disparate scenes undeterred by shadow effects, layover, noise and a host of other issues (i.e., *nuisance effects)* and ultimately determine the pertinent change areas. Therefore, the importance of the human cannot be understated (Radke, R., et. al., Mar 2005).

As mentioned before, the analyst ultimately identifies change; however, preprocessing algorithms such as geospatial registration is critical in reducing the analyst burden. Many semi-automated techniques leverage this as a first step. A common computational inexpensive technique, which highly leverages the presence of the human analyst and their inherent biological visual system, is Two Color Multi View (2CMV). This is a very rudimentary but an effective way of detecting change between a set of temporally different images with overlapping registered footprints. Simply, 2CMV is accomplished by applying the pixel intensities to the red spectrum of the RGB signal for the reference or earlier image and applying the blue and green spectrums to the later image.

Those sets of pixels that are the same between images yield a gray shaded pixel. Those pixels that are red indicate items that were in the reference but are missing from the later image. Blue-green pixels indicates new object not present in the reference. A mixture of colors indicates a more subtle change between images. An example is shown in Figure 1. This approach is rapid and can provide 2D awareness of what has changed over a large area. However, if the images are different in modality, i.e., *cross-sensor change detection,* then this approach is not as applicable. The coarseness of the DSM that the images are being projected can contribute error onto then Two Color Multi View result and yielding false positive changes. A better approach would utilize a High Resolution DSM that could better capture the true change in the AOI. We will show that the proposed solution is an excellent method for mitigating false positives. This point will be addressed later in Section 3.

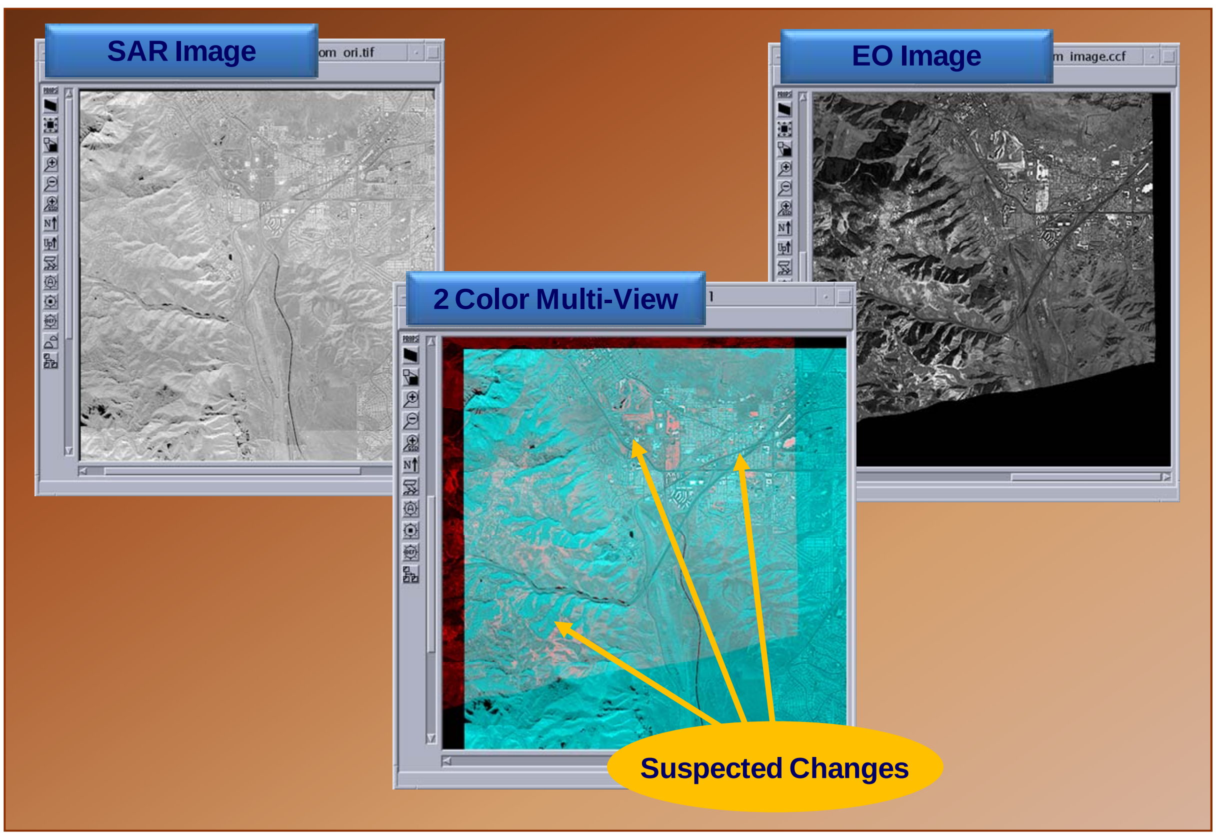

Figure 1. Two Color Multi-View

Although 2CMV can be used for Synthetic Aperture Data (SAR) to indicate large changes, a more powerful technique known as Coherent Change Detection (CCD) products may be available. CCD is done via the collection and comparison of a pair of coherently registered SAR images from approximately the same geometry collected at two different times (before and after an event). The result of this comparison is a product that can reveal subtle changes in the area such as vehicular tracks, mine, or barrier emplacement. However, due to the non-coherent properties of typical imagery, cross sensor coherent change detection such as EO and SAR is not possible.

The rapid interest in the generation and exploitation of 3D scene products (e.g., SiteModel, LiDAR models, high-res DSMs, etc.) has made it possible to use 3D Models with 2D solutions. Thus, we introduce a method of change detection whereby a collected image is compared to a reference (source) image extracted from a pre-existing 3D scene (SiteModel, LiDAR model, high-res DEM, etc.) through a synthetic camera viewpoint which is created and placed in the scene in such a way as to match the collected image sensor location and parameterization (e.g., field-of-view, hyper-spectral vs. monochromatic, etc.). Further, relevant known "real-world" phenomenology such as atmospheric and time-of-day effects, overall ground lighting/reflectivity properties (e.g., urban vs. dense forest) can be simulated in the scene before the reference image is extracted for enhanced change detection performance.

In the next section, Our Approach, we present change detection through a combined process of elevation model differences (3D) and imagery content (2D). We propose several ways to utilize 3D data in unison with 2D data to create three dimensional change products that will assist the analyst to make better actionable decisions while mitigating fatigue. We utilize what is known as nuisance effects (i.e., shadows due to collection and layover) to inform the analyst autonomously when change has taken place.

OUR APPROACH

General Flow

Figure 2 illustrates our general algorithmic approach. The work flow manger essentially runs the entire algorithmic flow. What we seek to do is semi-autonomously as well as autonomously queries and order data from a data store to create Digital Surface Models (DSM). Harris Corporation has a long history of expertise in creating High Resolution Terrain Information, i.e., High Resolution DSM, via Topographic Data Processing (TDP) (Rahmes, M., et. al., May 2007). Moreover, we could also produce a DSM from dense geiger or linear mode LiDAR points with our "points to DSM" algorithm in Harris' LiteSite® Tool. Once these DSMs are created, they can be compared with previously created overlapping DSMs, textured with imagery, and fused with vector data in what is called the 4D Change Detection Process. After the 4D change detection algorithm is complete, we can view the results in a 3D aware viewer. See Figures 10, 11 & 12.

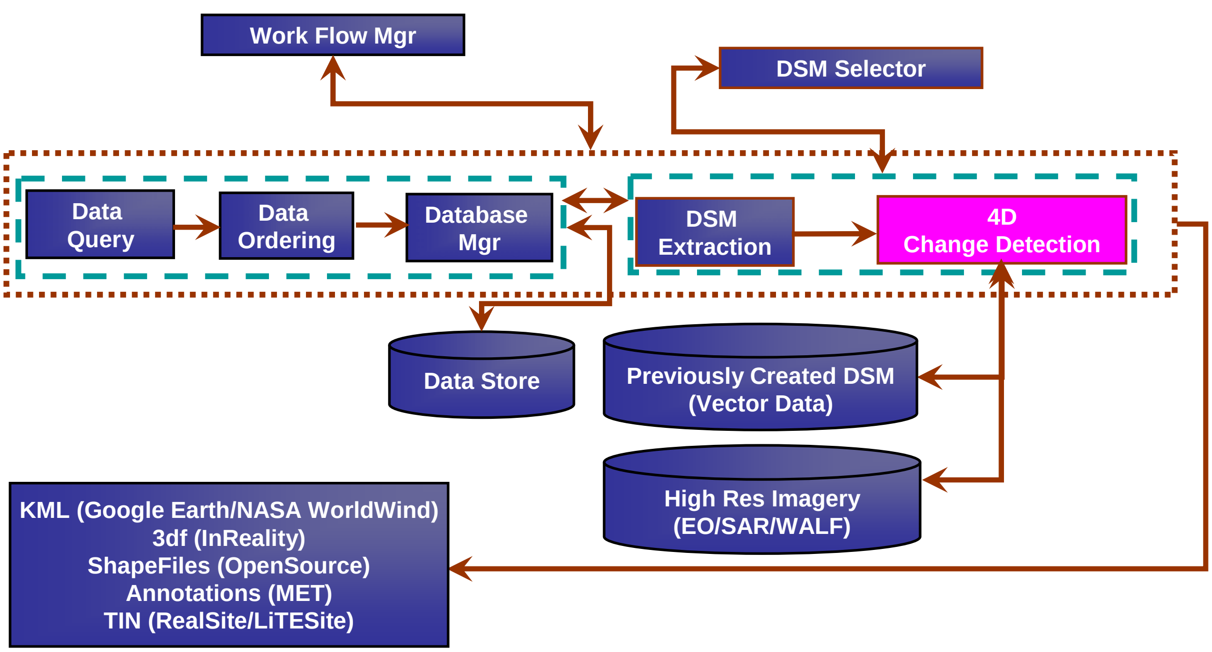

Figure 2. Illustration of our Change Detection Architecture

4D Change Detection

In the 4D Change Detection process, we feed in two overlapping 3D data files along with high resolution imagery of the scene. See Figures 3 & 4 for sample SAR and EO inputs. The underlying data used to create the DSM can be of different times and/or modalities (e.g., EO Correlated versus SAR Correlated). The outputs are a Change DSM, geo aware shape files, and annotations that are semi-autonomously mapped to the geo aware high resolution imagery (i.e., 2D data set) which overlaps the *residual* 3D *Cue* Change Detection DSM (the combined product we call *4D Change Detection*). See Figures 5 & 6 for examples of 4D Change Detection outputs. The fourth dimension is the situational awareness that an analyst obtains when rendering the scene. An example of this *Cue* Change DSM, also named *Q-DSM*, is the left side of Figure 5. The Q-DSM captures the spatial, and sometimes temporal, change between the initial Digital Surface Maps. We show that the Q-DSM will cue the analyst to where change has taken place. The Q-DSM is directly related to the initial Digital Surface Models that it was created from; thus, we have a direct geospatially aligned relationship between the Q-DSM and the original Digital Surface Maps. If one or both of the DSMs were created by a geospatial correlation process then we can map the Q-DSM back to the originating imagery. A novelty of this is implicit *Cross-Sensor Change Detection.* See Figure 5 for an example DSM Products, one created from SAR and another from EO imagery.

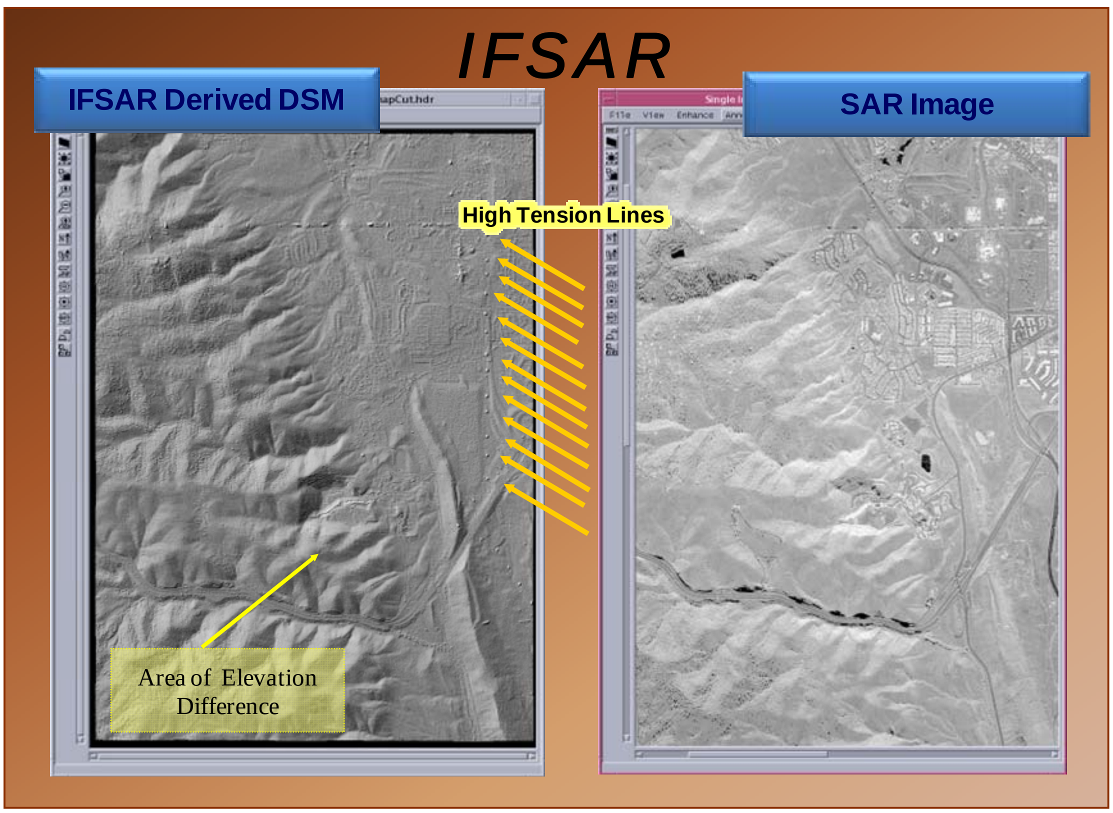

Figure 3. IFSAR inputs and associated computed DSM

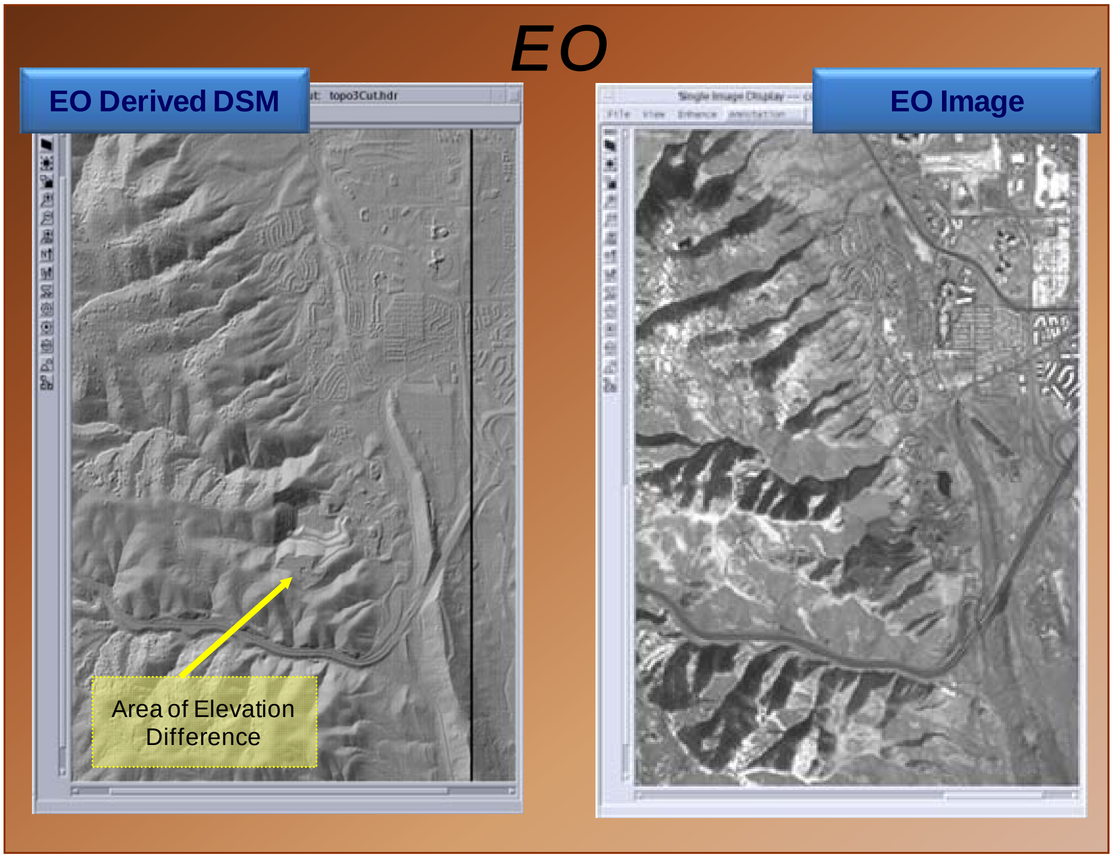

Figure 4. EO inputs and associated computed DSM

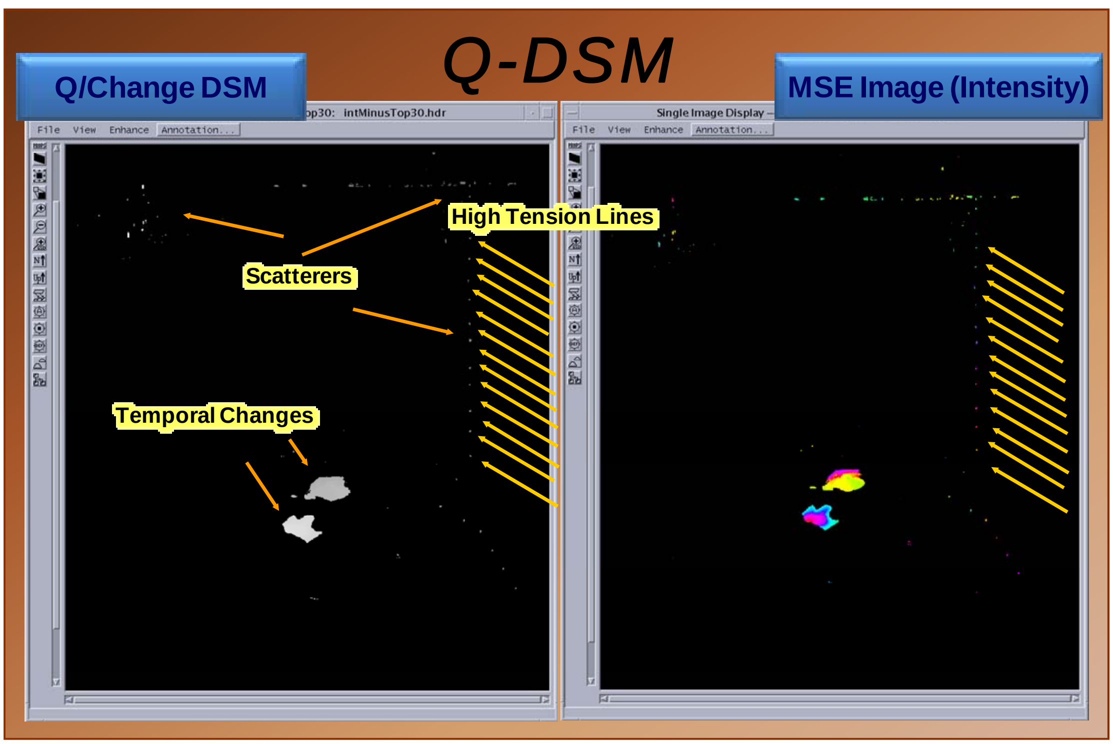

Figure 5. Q-DSM Outputs

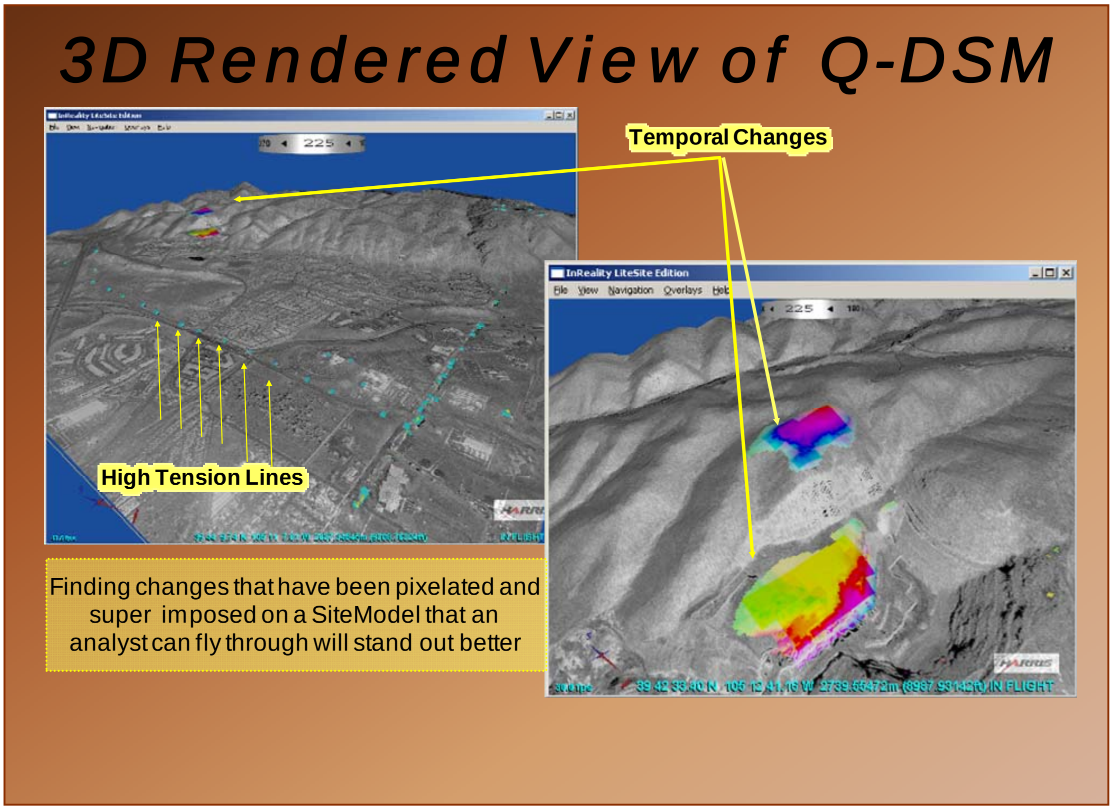

Figure 6. 3D Rendered View of Q-DSM

When combined to obtain a 4D change detection product (right side of Figure 5), these data sets illustrate two notions of change detection, i.e., temporal and modal. The temporal change yields an area of build-up or construction and the modality change yields *A-Frames*, (i.e., high voltage power line structures). It is important to note that EO correlated DSMs will not typically reveal A-Frames as they have a narrow base and therefore do not contribute significantly in the pixel correlations used to create the DSM. However, because of the radar cross section scattering effects encountered in SAR imagery, the metallic A-frames yield coherent correlations that are more than adequate to give rise to height information in an IFSAR derived DSM product. Another significant observation is that we can map any 2D geo-aware data set back to the Q-DSM. Changes in the Q-DSM are then mapped back to pixel space where we can perturb those pixels in a meaningful way. By meaningful, we refer to relative strength probability assessment as to the number of pixels that have changed in image space. To the point, we can reference the pixel data via the post spacing such that we can propagate the associated geospatial error related to the correlated DSM by sensor model parameters. Important to realize is that we are using the Q-DSM as a way to do *cross-sensor registration and ultimately cross-sensor change detection.*

3D Shadow

In addition, we have shown we can use knowledge of shadows in imagery to inform the analyst autonomously when change has taken place. This is done by calibrating the sensor model geometries such that they align better to pertinent 2D and 3D data sets, see Figure 7. Suppose that we have a known, trusted DSM and two overlapping images related to the DSM; the first image is truth. Let us further suppose that the second image was collected at a different time of the day. We can model the shadow effects in 3-Space and project those into to 2-Space. Hence, we can now model the shadow effects and thus, estimate layover effects. We, therefore, can use the knowledge of shadow to determine if there is true change between the first and second images. We name this approach *3D Shade.* See Figures 8 and 9 for examples in an urban area.

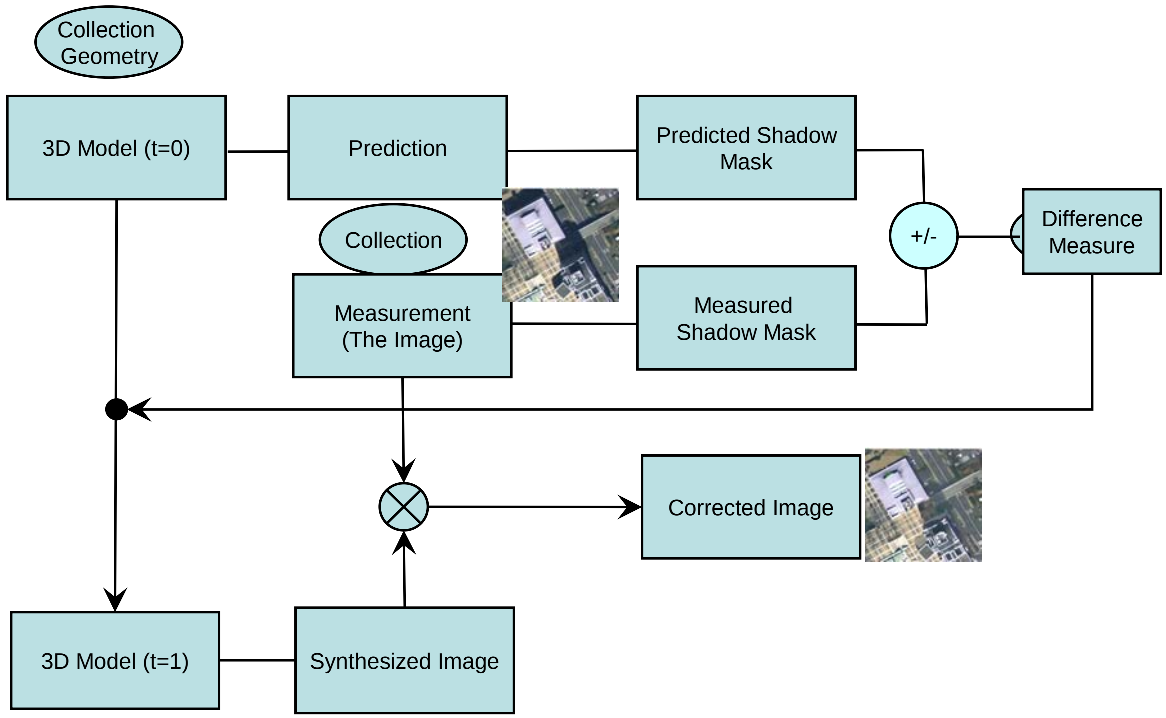

Figure 7. 3D Shade calculation using DSMs

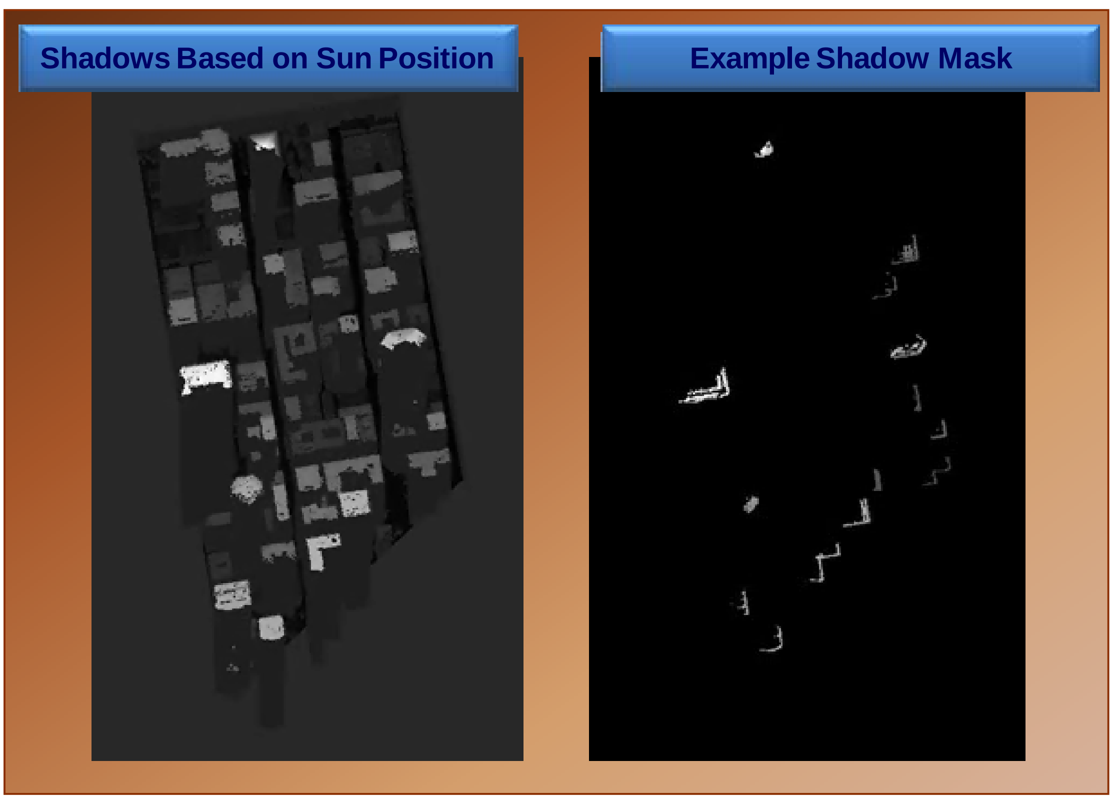

Figure 8. Shadow Based Imagery

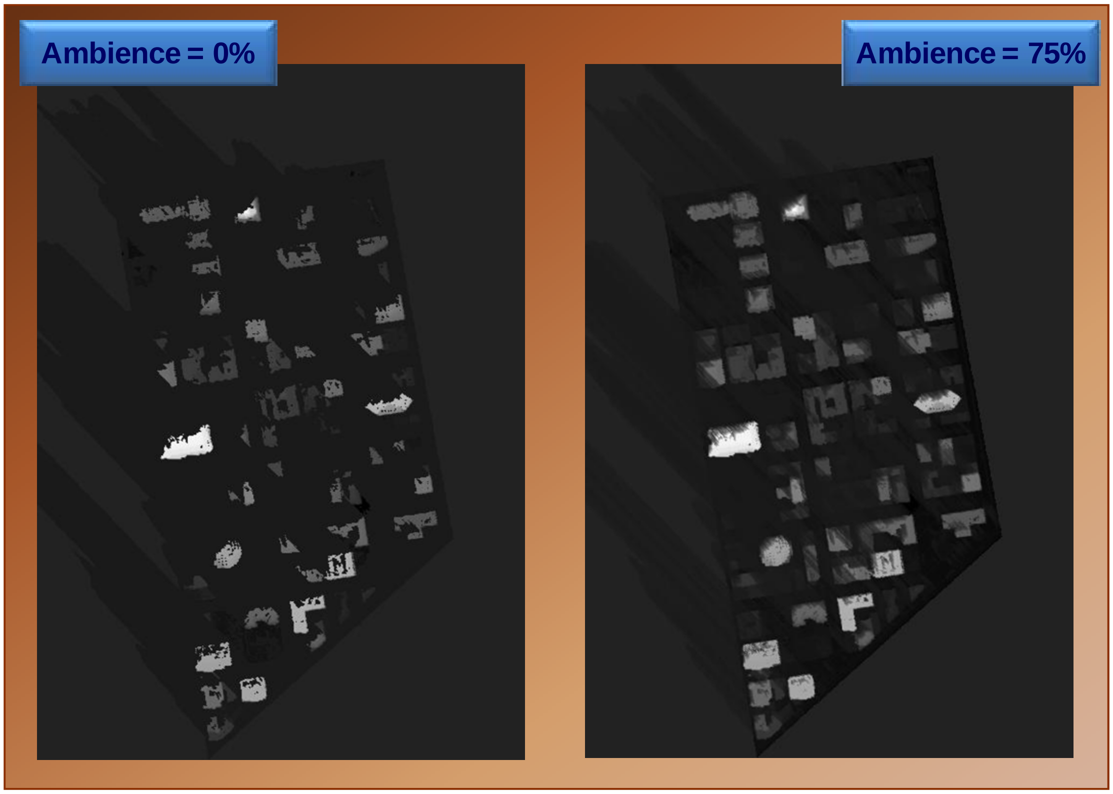

Figure 9. Ambience

CONCLUSIONS

We have shown how the fusion of disparate 2D and 3D data helps yield an actionable change detection product that uses multiple data sources to assist the analyst to do their job more accurately and effectively. We submit that utilizing the Q-DSM and 3D Shade process that the changes defined for the analyst will become more apparent and obvious. Hence, this will mitigate fatigue and enhance 3D visualization. This product will allow the analyst to quickly locate changes in a scene and visualize those changes in either Harris' COTS InReality Viewer (http://www.govcomm.harris.com/realsite/inreality.html), Google Earth (http://earth.google.com/) or NASA World Wind Environment (http://worldwind.arc.nasa.gov/), as shown in Figures 6, 11, and 12 respectively. Although not investigated, we suspect that this product could aid in CCD and Two Color Multi View (2CMV) product creation and given the right data sets, it could combine the two products together.

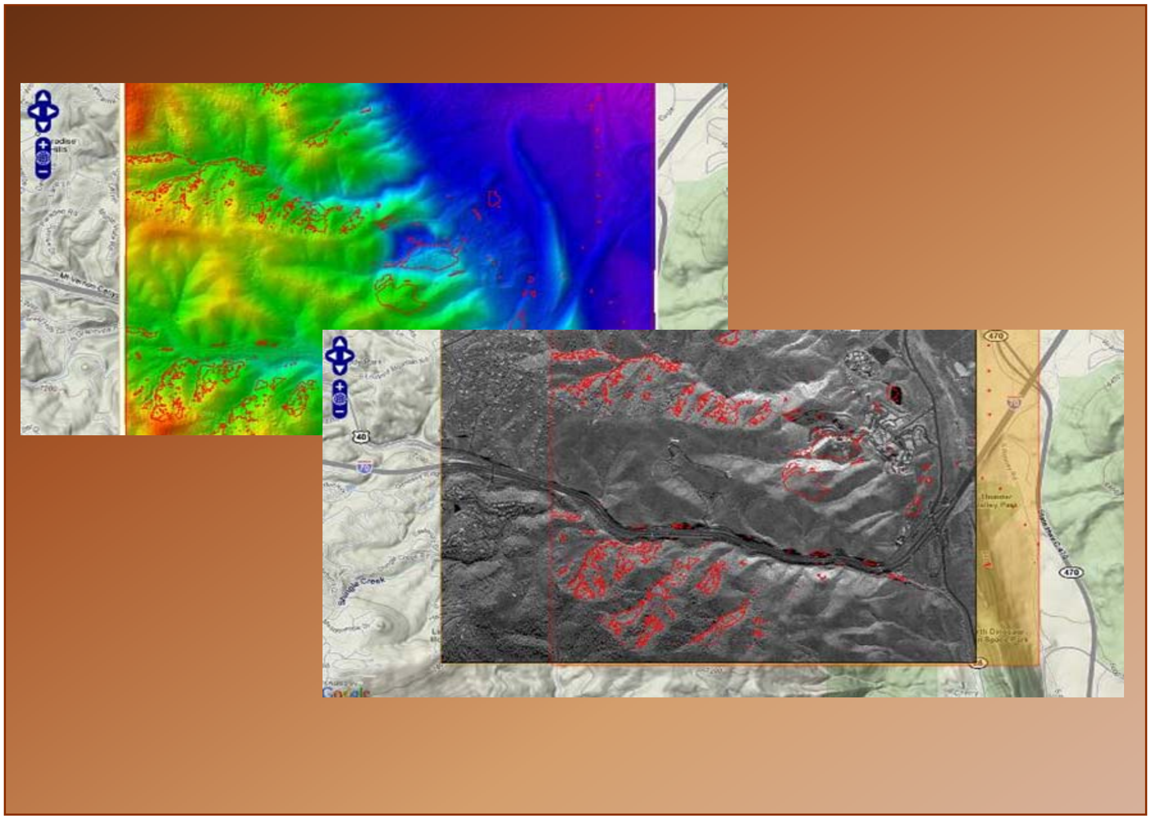

Figure 10. Results in 2D – areas of change indicated by red polygons

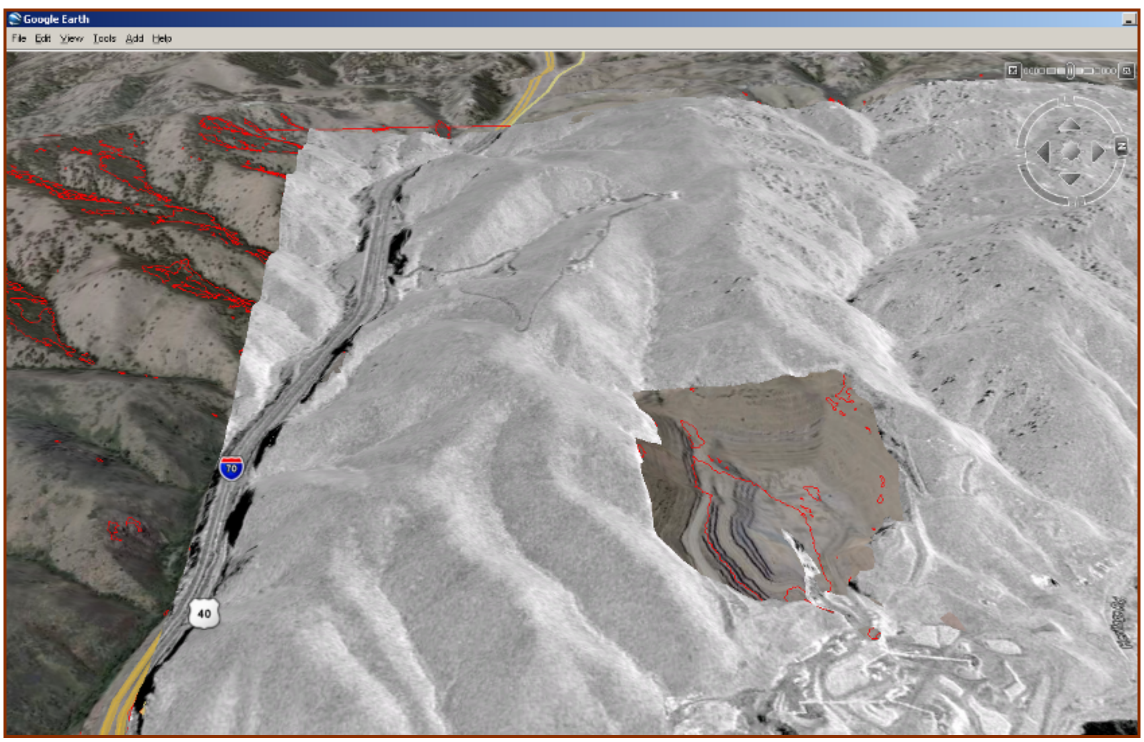

Figure 11. Google Earth with source data overlay – change indicated by red polygons

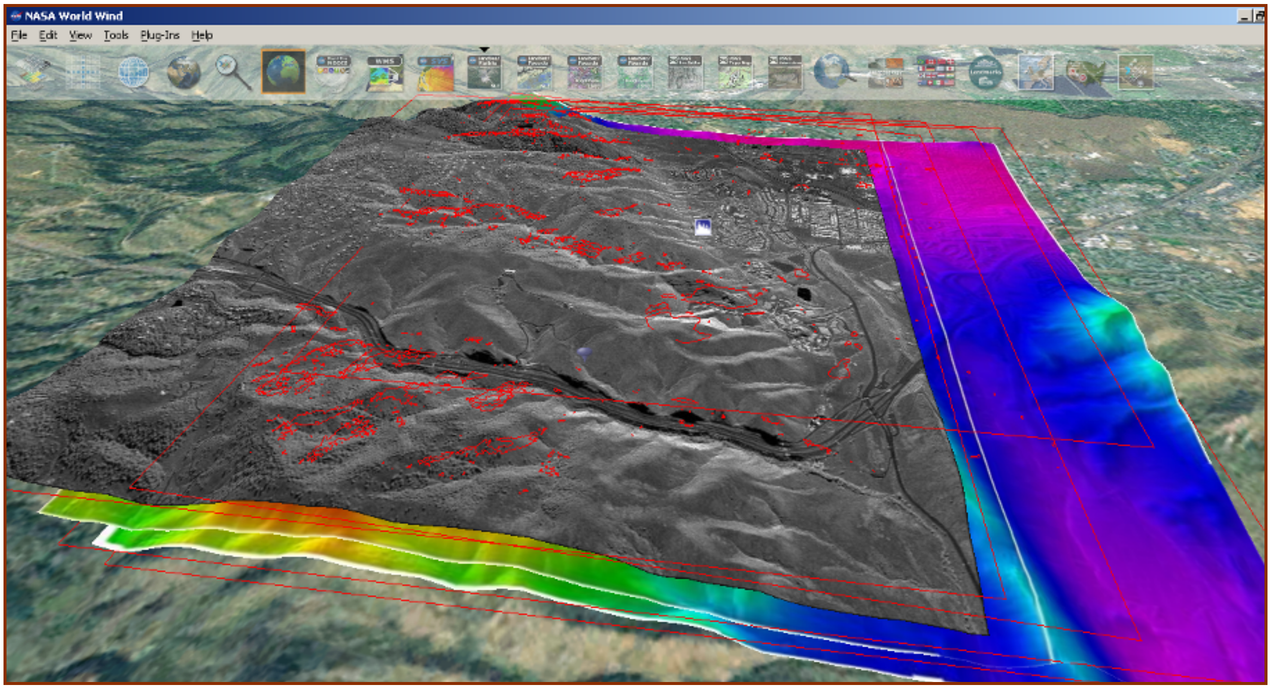

Figure 12. WorldWind with source data overlay – change indicated by non-uniform red polygons

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