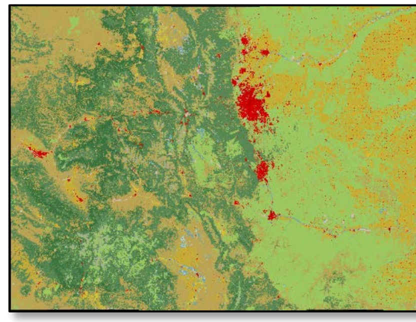
ColoradoView
2018 - 2019

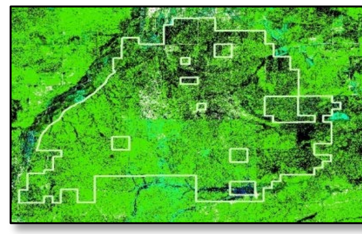
ColoradoView History and Successes

ColoradoView's broad objective is to facilitate innovative uses of Landsat and other USGS remote sensing data by students, educators and researchers in academia and government agencies who are working on issues that are important to the citizens of Colorado. ColoradoView (hereafter CV) addresses AmericaView's objectives of defining data requirements of the user community, establishing strategic partnerships to use GIS and remote sensing data and derivatives for education, research, and decision-making, and promoting research and remote sensing experience at the university level. During the previous grant cycle, CV has carried out the following research tasks.



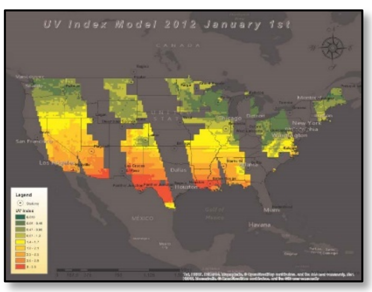
NLCD 30-m Landsat-based land cover map of Colorado (2016)

Invasive species: The research focused on predicting the spatial distribution of invasive species for Colorado using a maximum-entropy model and the inputs from remote sensing and other data sources. The model successfully predicted the potential range for the two invasive species (wheat stem sawfly and cheatgrass) in Colorado, and the MODIS greenness and fire data improved model performance.



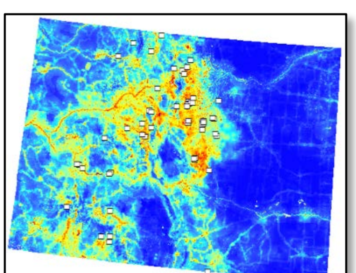
Colorado Sustainable Grazing—vegetation classification on the BX range

Distribution of UV-B radiation: The USDA UV-B Monitoring and Research Program (UVMRP) has a network of stations that measures UV radiation across the U.S. CV worked with the UVMRP program to use remote sensing data to produce improved maps of UV-B radiation. For Colorado, the improved maps can be combined with crop cover maps to estimate UV-B impacts on agriculture.



UV skin damage index map for a day

Grazing lands: The use of grazing lands is widespread in Colorado, both by domestic livestock and wildlife. Significant economic returns are realized by livestock producers, wildlife-based hunting, and tourism. CV worked with USDA and USGS to assess environmental impacts on grazing ecosystems, grazing impacts on vegetation and wildlife habitats, and appropriate management levels and carrying capacities. The developed utilities and procedures facilitated the use of Landsat, MODIS, and NAIP data in grazing land research.



Distribution of the Invasive Species (Yellow Toadflax)

Federal consortium members identified above do not receive funding from AmericaView.

ColoradoView is a member of the AmericaView Consortium, a nationally coordinated network of academic, agency, non-profit, and industry partners and cooperators that share the vision of promoting and supporting the use of remote sensing data and technology within each state. AmericaView is funded by USGS grant agreement G18AP00077.

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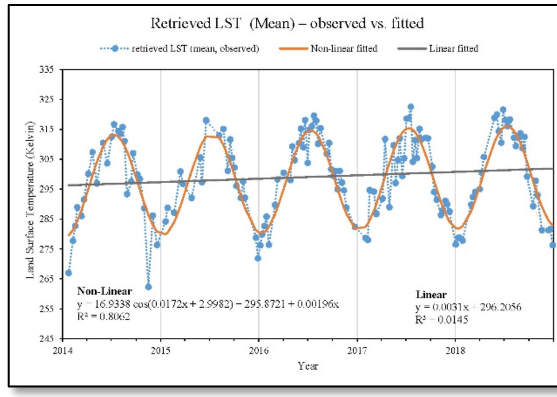
COLORADOVIEW 2018 - 2019 ACTIVITIES

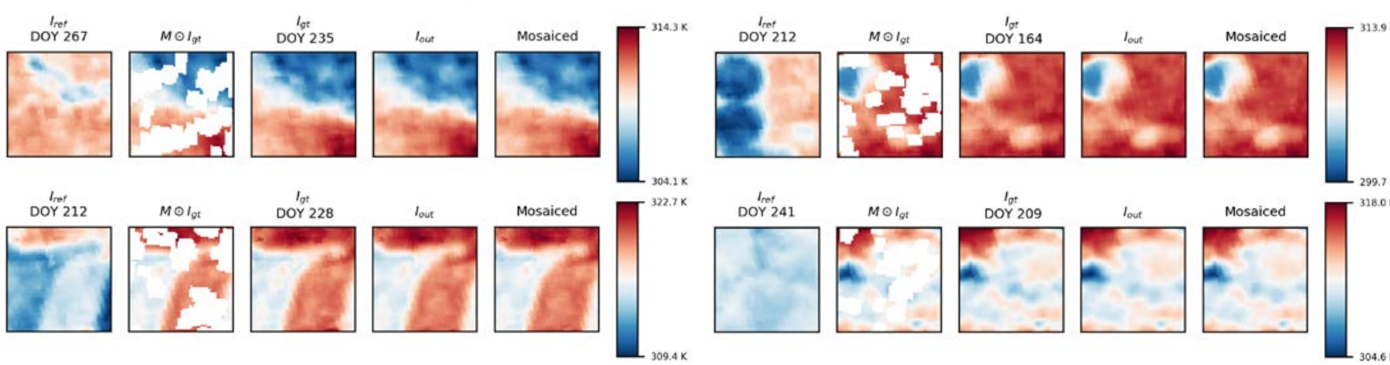
Water availability is the main controlling factor of plant growth and production in Colorado. As Land Surface Temperature (LST) is a critical variable to monitor Earth's surface energy and water balance (i.e., linking to water availability), this year ColoradoView's HIA focuses on obtaining accurate, high-resolution, and gap-filled LST maps.



Task 1. Daily average of LST retrieved from Landsat 8 B10 for Denver county between 2014 and 2018

The first task retrieves 30-m LST from Landsat 8 band 10 observations in Colorado between 2014 and 2018 using the single-channel algorithm developed by Jimenez-Munoz et al. (2009). The retrieval results are validated against the USGS Landsat 8 Analysis Ready Dataset at six CO counties (i.e., Denver, San Juan, Gilpin, Moffat, Elbert, and Phillips) representing the six dominant land use types (i.e., developed, barren, forest, shrub, grassland, crops) in Colorado. In general, the accuracy of the retrieved LST is high with the average RMSEs (outlier removed) at these counties between 0.58 and 1.15 K and the standard deviations between 0.21 and 0.90 K. The long-term LST trends over the 5-year period at these counties are small and not statistically significant.

The second task develops a partial-convolution based deep neural network with the U-Net like architecture to reconstruct the missing pixels in satellite images. The original partial convolution layer developed by Liu et al. (2018) is modified to consider both the convolution kernel weights and the number of valid pixels in the calculation of the mask correction ratio. In addition, the new partial merge layer is developed to merge feature maps according to their masks. Pixel reconstruction using this model was conducted using USGS Landsat 8 Analysis Ready Dataset (ARD) LST images in Colorado between 2014 and 2018. Complete LST patches (64 x 64 pixels) for two identical scenes acquired at different dates (up to 48 days apart) were randomly paired with ARD cloud masks to generate the model inputs. The model was trained for 10 epochs and the validation results show that the average RMSE values for a restored LST image in the unmasked, masked, and whole region are 0.29K, 1.00K, and 0.62K, respectively. In general, the model is capable of capturing the high-level semantics from the inputs and bridging the difference in acquisition dates for gap filling. The transition between the masked and unmasked regions (including the edge area of the image) in restored images is smooth and reflects realistic features (e.g., LST gradients). For large masked areas, the reference provides semantics at both low and high levels. This task has been summarized and published as the paper "Reconstruct missing pixels of Landsat land surface temperature product using a CNN with partial convolution" in the Proceedings of SPIE, Applications of Machine Learning, 2019.



Task 2. Four model validation examples. The subplots in each example from left to right refer to (1) the reference image (I_{ref}), (2) the to-be-recovered corrupted image ($M \odot Igt$), (3) the complete target image (ground truth, I_{gt}), (4) the raw model prediction (i.e., the raw reconstructed image, I_{out}), and (5) I_{comp}, the mosaic of the unmasked part of I_{gt} and the masked part of I_{out}.

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