Building Near-Real-Time MODIS Data Fusion Workflow to Support Agricultural Decision-making Applications

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***Abstract*—WaterSmart project is an NSF funded projected seeks water consumption reduction using satellite observations. In order to fit the fine temporal resolution requirement, satellites are required to have a high revisit cycle. MODIS is an ideal platform for monitoring the ground thanks to its daily coverage while the spatial resolution is too coarse. Research has demonstrated the possibility to improve the spatial resolution of MODIS using the Landsat 8 images. This research is aimed to establish a workflow to adapt the data fusion algorithm to achieve automatically processing at real-time in order to support short-term decision making.**

***Index Terms*—Agriculture, remote sensing, MODIS, data fusion, web service**

I. Introduction

Water is one of the most important resources for agricultural activities. Most farmlands were established near water sources such as rivers and lakes until irrigation system was invented [1]–[3]. With the development of the water grid and irrigation system, large scale farming became possible. However, the needs of water quantity varies for different soil type, plant conditions, and locations. To get accurate information on water consumption at field level, measurements need to be collected at field stations. To build many measuring stations could be economically inefficient, while data could be less accurate when there is no sufficient measurement across fields.

Remote sensing plays one of the most important roles in agricultural activities thanks to its large spatial coverage, frequent revisit cycle. and relative low cost [4]. Many research has demonstrate the feasibility of using remote sensing techniques to monitor agricultural activities [5]–[11]. However, remote sensing is not able to provide fine spatial and temporal observations at same time for large scale due to technology limitation [4]. Satellites are only capable to provide fine spatial resolution information when temporal resolution is coarse or footprint is small [4], [12]. For this reason, limited research was done to help farmer to make irrigation decision at field level for a large area.

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Image fusion was introduced to remote sensing community trying to get fine spatial and temporal resolution image at the same time by aggregating images from multiple satellites [13]. Many image fusion algorithms were developed; however, most of pervious research was mainly focus on the fusion algorithm which was not trying to bring the technology into real world applications [13]. This research tried to bring results from image fusion technology to real world application: 1) to test the feasibility of adopting image fusion in real world problem which needs to be addressed in near real time (NRT); 2) to build a workflow to facilitate automated data processing and dissemination using web services.

II. Background

To help the US Department of Agriculture reach its 2030 sustainable agriculture goals, the WaterSmart project was awarded by the National Science Foundation (NSF) to enhance food and energy security. The main goal of the project was focus on helping the farmer to save water during irrigation. Water plays an important role in energy used during crops production [14]. Irrigation during water shortage could help the growth of the crop, while over irrigation leads to energy and economic loss [6]. Farmers make irrigation decision every day based on the condition of crop and weather foresting. While weather foresting is usually accurate, the crop condition varies dramatically even at local level. The lack of understanding of such spatial variation brings difficult for farmers to irrigation decision, and could even reduce crop yield by over irrigating.

Nebraska was selected as the study area in this research thanks to its large scale of farmland and irrigation system. Center Pivot Irrigation System helped Nebraska became one of the top corn and soybean production states in the United States. To help farmers in Nebraska to reduce irrigation cost and increase crop productivity could be a good case study when promoting the solution to the entire nation.

III. Data and Algorithm

In this research, we try to combine existing image fusion algorithms from previous work and state-of-the-art GIS

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techniques together in order to support agricultural decision-making applications. This chapters will be discussing the data and algorithm used in this research and data used to support the algorithm.

Among public available datasets, Landsat and Moderate Resolution Imaging Spectroradiometer (MODIS) are two of the most popular data sources in scientific research and industrial applications thanks to their long temporal coverage and open data policy. Both satellites have been extensively used in agricultural studies. Landsat is widely used in crop identification and mapping, soil study, and other long term crop monitoring activities. On the other hand, MODIS is heavily used in near real time crop monitoring, natural disaster prediction and assessment thanks to its frequent revisit cycle.

To bring two satellite together is crucial for agricultural study since crop monitoring is significant and time sensitive during the growing season. For this reason, many image fusion algorithms were developed for remote sensing in the past few decades. Spatial Temporal Adaptive Algorithm for mapping Reflectance Change (STAARCH) was used in this research since this algorithm was designed for Landsat TM/ETM and MODIS images [15]. Image fusion is able to help improve temporal resolution for fine spatial resolution images by introducing other fine temporal resolution satellite; however, it is not able to provide more additional information to the data. In addition, using image fusion could introduce accuracy decrease, while in the testing result of the algorithm it loss about 7% of spatial information compares with validation set.

IV. Platform and Architectures

The fusion process will take large computation resources, thus a well-designed architecture is needed and a powerful platform is required to operate the proposed fusion algorithm. This chapter will be discussing on the geo-processing algorithms used in this research and the platform to facilitate these operations.

A. CSISS GeoBrain Cloud

Unlike many other agencies rely on commercial on-demand cloud infrastructure such as Amazon Web Service (AWS), the Center for Spatial Information Science and Systems (CSISS) developed a private cloud provide services mainly to EO data. The cloud was developed based Apache Cloud stack, and provide virtual machines to multiple operational services hosted by CSISS [16], [17]. Currently, there are more than 300 GPI cores, over 500GB rams and more than 500 TB storage and a cluster of NVIDIA Tesla K80 GPUs on the server and it continues expanding.

To ensure the safety and reliability of operational services, all machines are hosted at the CSISS Data Center, George Mason University. Figure 1 shows the current servers hosted in CSISS Datacenter. Thanks to its State-of-the-art UPS systems, the data center could provide continuous power support during a power interruption. Also, the center is being monitored 24 hours a day, 7 days a week to prevent any potential risk.

Fig. 1. The Servers supporting GeoBrain Cloud, CSISS Data center

B. Geoprocessing Architecture

Thanks to the inclusion of OGC WPS interface standards (WPS2.0) in the GeoBrain cloud, we can efficiently build algorithm to utilize such tools efficiently in the cloud [16], [18]–[20]. In this research, a workflow was designed to utilize such cloud environment to process near real time (NRT) image fusion and real time client/server interaction.

Figure 2 shows the high level architecture design for the geoprocessing task. Based on the client request, the program will automatically download and process the data and perform the fusion. In the end, it will provide the fused image back to the client. As this research is supporting the waterSmart project, the current program only supports Nebrask state. Further enhancements are planned to be implemented in the future.

C. Server/Client Architecture

The communication between client and server is established on the WaterSmart application. Basically the client could send fusion request on WaterSmart platform, and the platform will pass the request to the geoprocessing program and the result will be sent back to the client through OGC standard web-services (Figure 3) [21]–[23]. Since the response is standard, the client can be either a human user or machine user [17], [24]. Here is one example of the final product back to the user: http://129.174.131.6/cgi-bin/mapserv?SRS=EPSG%3A102004&LAYERS=P030R031_20181125&MAP=%2Fhome%2Fllin%2Ffusion%2Fmapfile%2FP030R031%2FP030R031_20181125.map&FORMAT=image%2Fpng&TRANSPARENT=true&SERVICE=WMS&VERSION=1.1.1&REQUEST=GetMap&STYLES=&EXCEPTIONS=application%2Fvnd.ogc.se_inimage&BBOX=-378299.208,1964729.214,-139380.675,2210401.097&WIDTH=256&HEIGHT=256

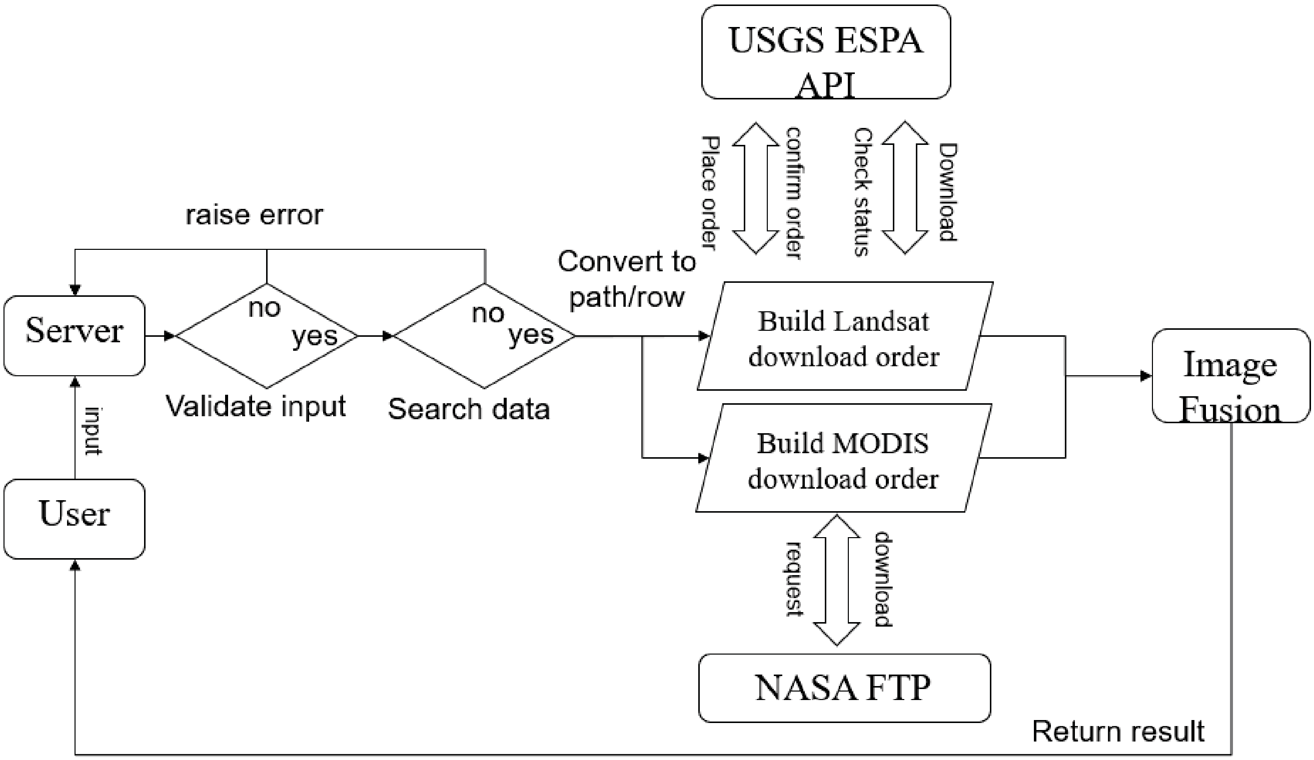

Fig. 2. Geoprocessing architecture for NRT MODIS image fusion

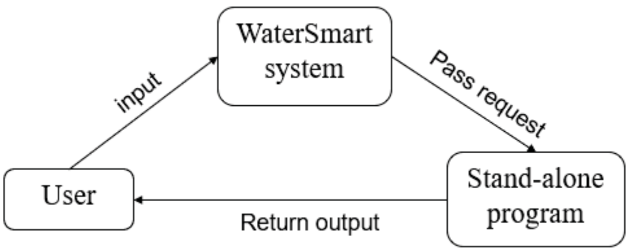

Fig. 3. Client and Server Interaction Architecture

V. Results

This research tried to bring image fusion algorithms and state-of-the-art geoprocessing techniques together. First of all, the proposed architecture was successfully deployed and executed. Figure 4 shows the NRT MODIS image for grey colored farmland in Nebraska state on November 25, 2018. Figure 5 shows the result after applying the fusion algorithm.

As an experimental project runs on the GeoBrain cloud, the algorithm is able to reduce the processing time significantly compare with a standalone workstation. In addition, with the utilization of the private cloud developed by CSISS, clients could be accessing the result through standard web-services. For this reason, clients could not only download fused images, but also the produced fused images could be working with other data thru web-service as well.

VI. Conclusion and Future Work

This paper proposes a framework to develop a web service based application for Near Real Time MODIS data fusion to support Agricultural decision-making applications. This research introduced the data pre-processing, fusion algorithms, server & client interaction, and a series of state-of-the-art webservices. Both fusion algorithms and geoprocessing tested in this research have been widely used in the GIS industry; however, a good platform is needed to bring these two together to build a reliable operational application. GeorBrain, which was developed by CSISS became one of the most suitable platforms for the waterSmart project.

The research successfully developed a workflow to bring these services and algorithms together to support real life applications. Example field images were also tested for visual comparison, and a standard OGC WMS link was distributed for public testing in the paper. The workflow developed in this research is going to be free to be used by the public after the release of waterSmart portal.

Current version of fusion application supports accessing, visualizing, and generating the MODIS/Landsat fusion. In the future, we will process more historical fusion data to improve the data range. Furthermore, the processing time for the existing workflow still takes a few hours to finish

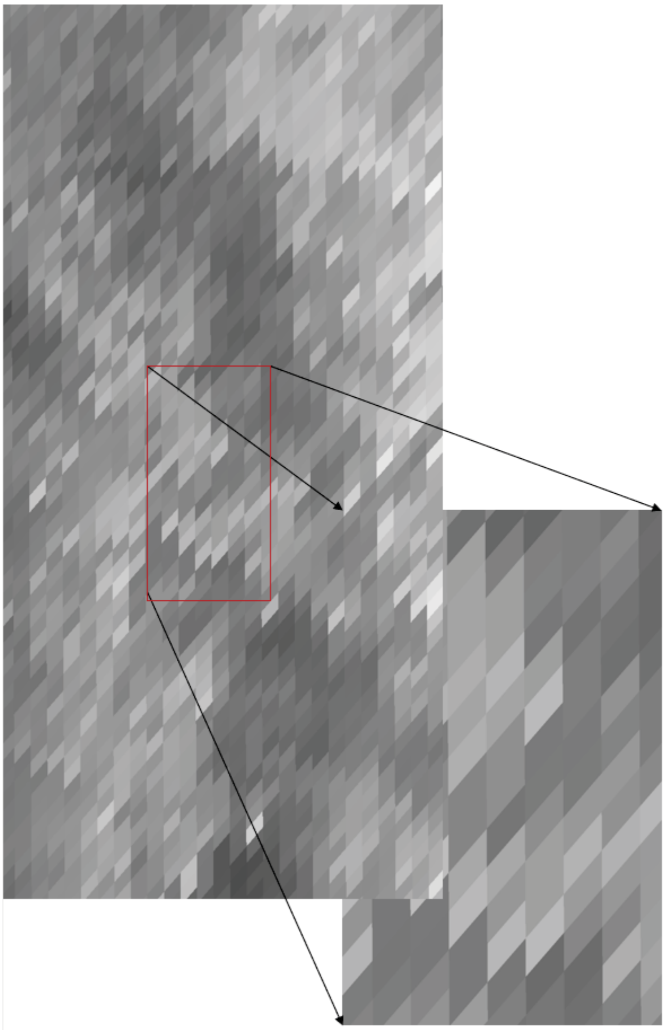

Fig. 4. NRT MODIS image for farmland in Nebraska state on November 25, 2018 (grey color)

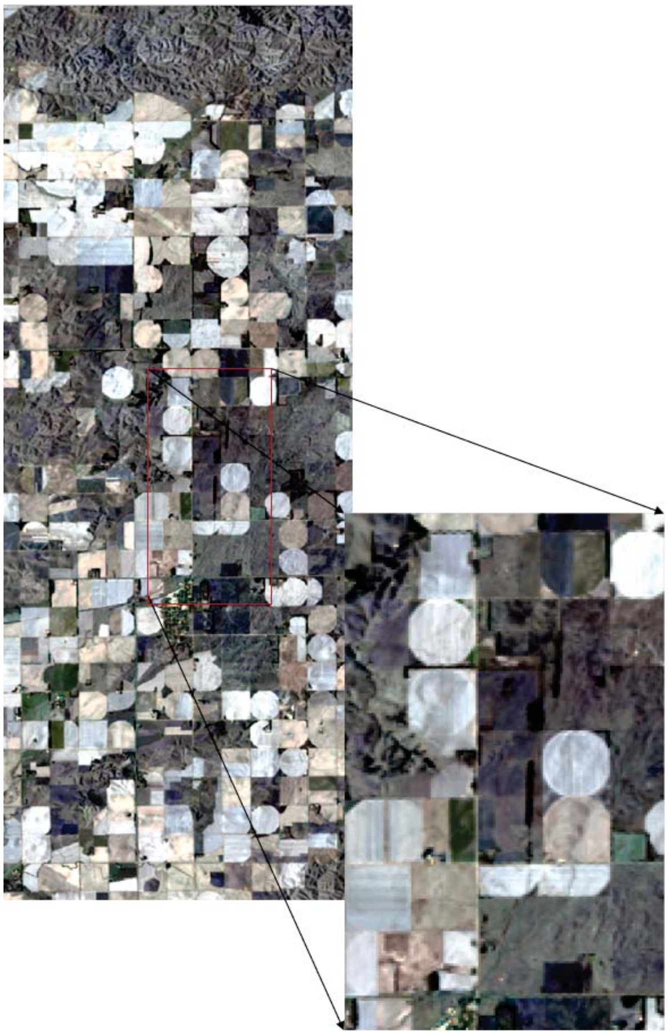

Fig. 5. Fused NRT MODIS image for farmland in Nebraska state on November 25, 2018 (false color)

one MODIS image. It is needed to provide faster processing solutions in the future for better user experience.

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