

Chapter 5

Cloud-Based Geo-Information Infrastructure to Support Agriculture Activity Monitoring

Shamim Akhter

East West University, Bangladesh

Kento Aida

NII, Japan

ABSTRACT

Agriculture activity monitoring needs to deal with large amount of data originated from various organizations (weather station, agriculture repositories, field management, farm management, universities, etc.) and mass people. Therefore, a scalable environment with flexible information access, easy communication and real time collaboration from all types of computing devices, including mobile handheld devices as smart phones, PDAs and iPads, Geo-sensor devices, and etc. are essential. It is mandatory that the system must be accessible, scalable, and transparent from location, migration and resources. In addition, the framework should support modern information retrieval and management systems, unstructured information to structured information processing (IBM Info Stream, text analytic, pig & hive, etc.), task prioritization, task distribution (Hadoop), workflow and task scheduling system, processing power and data storage (Amazon S3 and Google BigTable). Thus, High Scalability Computing (HSC) or Cloud based system can be a prominent and convincing solution for this circumstance.

INTRODUCTION

Agricultural activity monitoring, enclosed quantifying the irrigation scheduling, tracing the soil hydraulic properties, generating the crop calendar, prediction on crop growth in terms of planting date, acreage, planting intensity, water stress, biomass, yield etc., is very important. It can also contribute to better policymaking, timely countermeasures, optimization of water resources distributions, damage assessment and finally to food supply security and stable market. Farmers want to know the above information in a regular basis. Researchers of agriculture also try to analyze various information about crops in order to

DOI: 10.4018/978-1-5225-0539-6.ch005

take measures if they had some problems. Particularly, when an on-going experiment covers large area such as a country, Remote Sensing (RS) plays a vital role by providing useful information over large areas. However, some information, or crop parameters, e.g. ground water level, cropping season time extent, date of emergence of crop, irrigation scheduling cannot be visible directly through RS images, which reflects a practical problem that we cannot generate or observe those parameters from remote places. To collect those data, time by time basis field experiments are required. This is a time consuming, complex and expensive procedure. To overcome such problems, indirect methods such as inverse modeling with crop model can be used to obtain those basic input parameters. One such method is the manual calibration by “trial and error” procedure, which is very subjective and time consuming and uncertainty associated with them cannot be quantified. A more robust way of inverse modeling is to combine the model with optimization algorithm. However, processing the inverse modeling with crop model has a problem in practicality, that is, they require a huge amount of processing times. It becomes necessary to introduce methods for using higher processing power such as High Performance Computing (HPC) technologies. Some protocols or tools have been developed concerning the inverse modeling techniques and their HPC implementation models. However, the interoperability protocol between those agriculture applications and existing remote sensing (RS) image processing software is also necessary to improve practicality.

Inverse Modeling Techniques

Crop models, Soil-Water-Air-Plant (SWAP) (Van Dam et al., 1997) or Decision Support System for Agro technology Transfer (DSSAT) (Tsuji et al., 1994), have capacity to simulate soil, water and crop processes and serve as crop productivity monitoring tool. Crop Assimilation Model (CAM) predicts parameters of crop models with satellite images. A new methodology was developed in (Ines, 2004), CAM-GA, to analyze the crop model (SWAP) parameters assimilation with Remote Sensing (RS) data and that parameters assimilation procedure was optimized by an evolutionary searching technique called Genetic Algorithm (GA). CAM with double layers GA, CAM-DLGA (Akhter et al., 2010b), uses directly visible multi-resolution RS images (ASTER Image Webpage, 2009) (MODIS Image Webpage, 2009) and inversely assimilates to SWAP model data for estimating the non-visible model parameters. Other similar functionality models, e.g., CAM-PSO (Kamble & Chemin, 2006) and CAM-PEST (Dorji, 2003), use different evolutionary searching techniques. However, processing the agricultural information with CAM has a problem in practicality, that is, they require a huge amount of processing times. It becomes necessary to introduce methods for using higher processing power such as High Performance Computing (HPC) technologies.

High Performance Computing Issues

Multi computer based distributed systems (Clusters and Grids) have a large processing capacity for a lower cost; naturally, choice turns towards developing HPC applications. However, it is not an easy job to port CAM in HPC environment. The application performance is significantly affected by the data and task distribution methods on the HPC and developers of agriculture or satellite image processing applications need to solve the problem of both data and task distribution, or how to distribute data and tasks among single or multiple clusters environment. The workload in HPC, the bandwidth, the processors speed, parameters of evaluation methods and data size are additional concerning factors. CAM-GA Model in successfully implemented on cluster computers and the implementation strategies are described

8 more pages are available in the full version of this document, which may be purchased using the "Add to Cart" button on the publisher's webpage:

www.igi-global.com/chapter/cloud-based-geo-information-infrastructure-to-support-agriculture-activity-monitoring/160572

Related Content

Towards the Blanket Coverage DNA Profiling and Sampling of Citizens in England, Wales, and Northern Ireland

Katina Michael (2014). *Ubervveillance and the Social Implications of Microchip Implants: Emerging Technologies* (pp. 187-207).

www.irma-international.org/chapter/towards-the-blanket-coverage-dna-profiling-and-sampling-of-citizens-in-england-wales-and-northern-ireland/95994

Higher Education Students Perspective on Education Management Information Systems: An Initial Success Model Proposal

José Martins, Frederico Branco, Manuel Au-Yong-Oliveira, Ramiro Gonçalves and Fernando Moreira (2019). *International Journal of Technology and Human Interaction* (pp. 1-10).

www.irma-international.org/article/higher-education-students-perspective-on-education-management-information-systems/222707

Location-Based Mobile Storytelling

Jennifer Stein, Scott Ruston and Scott S. Fisher (2011). *Sociological and Philosophical Aspects of Human Interaction with Technology: Advancing Concepts* (pp. 182-190).

www.irma-international.org/chapter/location-based-mobile-storytelling/54138

Adoption of Digital Art NFTs in Hong Kong

Sze Wing Wong, Mimi Mei Wa Chan and Dickson K. W. Chiu (2023). *Emerging Technology-Based Services and Systems in Libraries, Educational Institutions, and Non-Profit Organizations* (pp. 151-174).

www.irma-international.org/chapter/adoption-of-digital-art-nfts-in-hong-kong/328670

'Listening to the Voices of the Users' in Product Based Software Development

Netta Iivari and Tonja Molin-Juustila (2011). *Sociological and Philosophical Aspects of Human Interaction with Technology: Advancing Concepts* (pp. 157-181).

www.irma-international.org/chapter/listening-voices-users-product-based/54137