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HIGH-PERFORMANCE INTELLIGENT COMPUTATIONS FOR ENVIRONMENTAL AND DISASTER MONITORING

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Abstract: In this paper we present different approaches to multi-source data integration for the solution of complex applied problems, in particular flood mapping and vegetation state estimation using satellite, modelling and in-situ data. Since these applications are data- and computation-intensive, we use Grid computing technologies. In such a case computational and informational resources are geographically distributed and may belong to different organisations. For this purpose, we also investigate benefits of different approaches to the integration of satellite-based monitoring systems.

Keywords: data integration, Earth observation, flood mapping, inverse modelling, neural network, Grid technologies, information system, geospatial information.

ACM Classification Keywords: I.5.1 [Pattern Recognition] Models – Neural nets; G.1.8 [Numerical Analysis] Partial Differential Equations - Inverse problems; D.2.12 [Software Engineering] Interoperability; F.1.2 [Theory of Computation] Modes of Computation - Parallelism and concurrency; F.1.1 Models of Computation - Probabilistic computation; G.4 Mathematical Software - Parallel and vector implementations; H.1.1 [Information Systems] Models and Principles - Systems and Information Theory; H.3.5 [Information Storage and Retrieval] Online Information Services; I.4.6 [Image Processing and Computer Vision] Segmentation - Pixel classification; I.4.8 Scene Analysis - Sensor fusion; J.2 [Computer Applications] Physical Sciences and Engineering - Earth and Atmospheric Sciences

Introduction: Specifics of Earth Observation Problems

Nowadays, due to global climate change the solution of such problems as rational land use, environmental monitoring, prediction of natural disasters and so forth became the task of a great importance. The basis for the solution of these problems lies in the integrated use of data from multiple sources: modelling data, in-situ measurements and remote sensing observations. However, inconsistency of heterogeneous data and measurement techniques, spectral, spatial and temporal disarrangement of data limit the potential of up-to-date technologies for the solution of crucial problems of arising in the different social benefit areas. Therefore, there is a considerable need for the development of methods and technologies for integration of heterogeneous data coming from multiple sources.

Recent advances in satellite and sensor technologies made the Earth Observation (EO) data from space to play a major role in the solutions of applied problems in different domains. Satellite observations enable acquisition of data for large and hard-to-reach territories, and can provide continuous measurements and human-independent information. Such important applications as monitoring and prediction of floods, droughts, vegetation state assessment heavily rely on the use of EO data from space. For example, the satellite-derived flood extent is very important for calibration and validation of hydraulic models to reconstruct what happened during the flood and determine what caused the water to go where it did [Horritt, 2006]. Information on flood extent provided in the near real-time (NRT) can be also used for damage assessment and risk management, and can benefit to rescuers during the flooding. Both microwave and optical data can provide means to detect drought conditions, estimate drought extent and assess the damages caused by droughts [Kogan et al., 2004; Wagner et al., 2007].

It should be also emphasized that the same EO data sets and derived products can be used for a wide variety of applications. For example, land use/change information, soil properties and meteorological conditions are both important for floods and droughts applications as well as vegetation state assessment. That is, once the corresponding interfaces are developed to enable access to these data and products they can be used in a uniform way for different purposes and applications. Services and models that are common for different EO applications (e.g. flood monitoring and crop yield prediction) are shown in Fig. 1.

The EO domain, in turn, is characterized by large volumes of data that should be processed, catalogued, and archived. For example, GOME instrument onboard Envisat satellite generates nearly 400 Tb data per year [Fusco et al., 2003]. The processing of satellite data is carried out not by the single application with monolithic code, but by distributed applications. This process can be viewed as a complex workflow (DEGREE) that is composed of many tasks: geometric and radiometric calibration, filtration, reprojection, composites construction, classification, products development, post-processing, visualization, etc. [Rees, 2001].

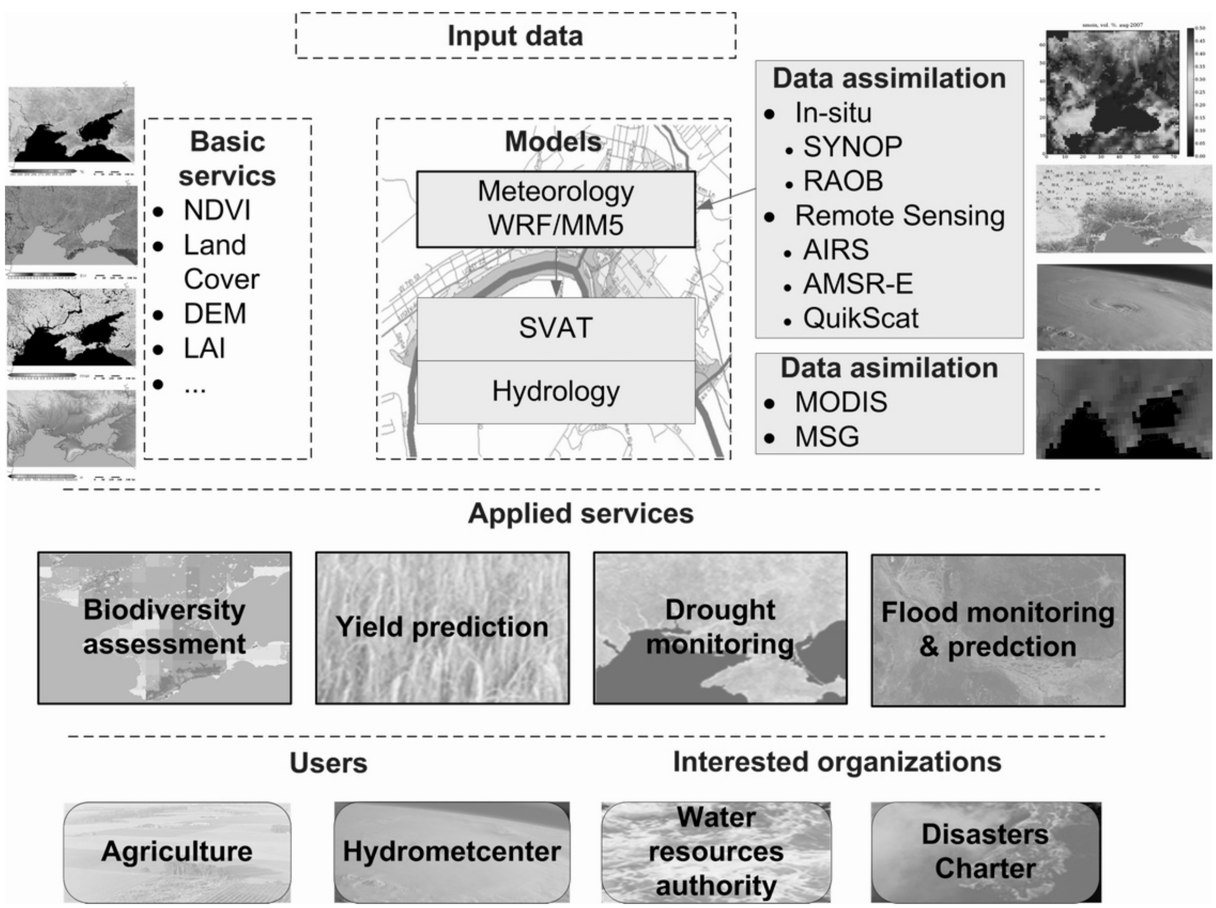


Figure 1. Common services and models for a variety of applications

To enable processing and management of such volumes of data sets and information flows an appropriate infrastructure is needed that will support [Fusco et al., 2003; Shelestov et al., 2006]: access to distributed resources; high flexibility; portal enabling easy and homogeneous accessibility; collaborative work; seamless integration of resources and processes; allow processing of large historical archives; avoid unauthorised access to/use of resources.

Grid can provide appropriate facilities for high-performance computations and efficient data management in EO domain. Grid computing is an emerging paradigm for global computing and a very active research domain for complex, dynamic, distributed and flexible computing and resource sharing [Foster and Kesselman, 2004]. Grid computing belongs to main trends of on-line environment development among with web services, semantic web and peer-to-peer networking. The integration of these technologies is essential for the next generation networks.

Grid systems are recognized to be very efficient for EO and geospatial community for a number of reasons: geospatial data and associated computational resources are naturally distributed; the multi-discipline nature of geospatial research and applications requires the integrated analysis of huge volume of multi-source data from multiple data centres; most geospatial modelling and applications are both data and computational intensive.

In this paper we present different approaches to multi-source data integration for the solution of complex applied problems, in particular flood mapping and vegetation state estimation using satellite, modelling and in-situ data. Since these applications are data- and computation-intensive, we use Grid computing technologies. In such a case computational and informational resources are geographically distributed and may belong to different organisations. For this purpose, we also investigate benefits and approaches to the integration of satellite-based monitoring systems.

The rest of the paper is organised as follows. First, we briefly review the existing Grid-systems for EO data processing. Then we describe in details two applications that are solved using multi-source data integration, and have been ported into Grid platform at the Space Research Institute NASU-NSAU. Then, we focus on the integration of geographically distributed information systems that rely on the use of EO data and implemented using Grid computing technologies.

State of the Art: Grid-based Systems for EO Data Processing

At present, Grid technologies are widely applied in different domains, in particular EO domain. The European DataGrid Project (EDG) was the first large European Commission-funded grid project (www.eu-datagrid.org) [Fusco et al., 2003]. Many of the results of EDG project have been included in the European project Enabling Grids for E-sciencE (EGEE). EGEE aims to develop a service grid infrastructure which is available to scientists 24 hours-a-day (http://www.eu-egee.org). Now EGEE and other existing Grid infrastructures in Europe are transitioned to the European Grid Initiative model (http://web.eu-egi.eu).

Based on the gained experience ESA and the European Space Research Institute (ESRIN) have developed Grid Processing on Demand (G-POD) for Earth Observation Applications (http://gpod.eo.esa.int). Online access to different data is enabled within this project, in particular to data provided by various instruments onboard Envisat satellite (http://envisat.esa.int), SEVIRI instrument onboard MSG (Meteosat Second Generation) satellite, ozone profiles derived from GOME instrument, etc. One of the most important applications is the analysis long-term data. Grid Web Portal provides access to the “Grid-on-demand” resources enabling: personal certification, time/space selection of data directly from the ESA catalogue, data transfer, job selection, launching and live status, data visualization.

A major challenge for DEGREE (Dissemination and Exploitation of GRids in Earth science, http://www.eu-degree.eu) project was to build a bridge linking the Earth Science and GRID communities throughout Europe, and focusing in particular on the EGEE-II Project. Grid provides appropriate infrastructure enabling international cooperation within GMES and GEOSS. The following problems were within the scope of DEGREE: earthquake analysis, floods modelling and forecasting, influence of climate changes on agriculture

Japan Aerospace eXploration Agency (JAXA) and KEIO University started establishing “Digital Asia” system aimed at semi-real time data processing and analyzing. They use GRID environment to accumulate knowledge and know-how to process remote sensing data. The Digital Asia project is the part of bigger Sentinel Asia project that is targeting on building natural disasters monitoring system Fukui, 2007].

CEOS Wide Area Grid (WAG) project was initiated by the CEOS Working Group on Information Systems and Services (WGISS), and aims at providing horizontal infrastructure enabling efficient integration of resources of different space agencies. WAG testbed infrastructure is currently under development within ESA Cat-1 project “Wide Area Grid Testbed for Flood Monitoring Using Spaceborne SAR and Optical Data” (no. 4181) [Kopp et al., 2007]. Within the WAG project Space Research Institute NASU-NSAU has developed a testbed that integrates resources of Ukrainian Grid segment (Ukrainian Academician Grid) with resources of international organisations (ESA, CEODE-CAS). The tesbed is described in more details in the subsequent sections.

Applications

In this section we focus on the detailed description of the two applications that are solved within Grid environment at the Space Research Institute NASU-NSAU:

- flood mapping from synthetic-aperture radar (SAR) satellite imagery, and
- vegetation state estimation using remote sensing and modelling data.

Flood Mapping from Satellite Imagery. In recent decades the number of hydrological natural disasters has considerably increased. According to [Scheuren et al., 2008], we have witnessed in recent years a strengthening of the upward trend, with an average annual growth rate of 8.4% in the 2000 to 2007 period. Hydrological disasters, such as floods, wet mass movements, represent 55% of the overall disasters reported in 2007, having a tremendously high human impact (177 million victims) and causing high economic damages (24.5 billion USD) [Scheuren et al., 2008].

EO data from space can provide valuable and timely information when one has to respond to and mitigate such emergencies as floods. From satellite imagery we can determine flood areas, since it is impractical to provide such information through field observations. The use of optical imagery (in visible and infra-red range) for flood mapping is limited by severe weather conditions, in particular by the presence of clouds. In turn, synthetic aperture radar (SAR) measurements from space are independent of daytime and weather conditions and can provide valuable information to monitoring of flood events. This is mainly due to the fact that smooth water surface provides no return to antenna in microwave spectrum and appears black in SAR imagery [Rees, 2001].

Flood mapping procedure from SAR imagery represents a complex workflow and consists of the following steps. The first step consists in re-constructing a satellite imagery taking into account the calibration, the terrain distortion using digital elevation model (DEM) and providing exact geographical coordinates. The second step is image segmentation, and the third step consists in the classification to determine the flood extent.

In this subsection we describe a neural network approach to flood mapping from satellite SAR imagery that is based on the application of self-organizing Kohonen's maps (SOMs) [Kohonen, 1995; Haykin, 1999]. The advantage of using SOMs is that they provide effective software tool for the visualization of high-dimensional data, automatically discover of statistically salient features of pattern vectors in data set, and can find clusters in training data pattern space which can be used to classify new patterns [Kohonen, 1995]. We applied our approach to the processing of data acquired from different satellite SAR instruments (ERS-2/SAR, ENVISAT/ASAR, RADARSAT-1 and RADARSAT-2) for different flood events: river Tisza, Ukraine and Hungary (2001); river Huaihe, China (2007); river Mekong, Thailand and Laos (2008); river Koshi, India and Nepal (2008); river Norman, Australia (2009); and river Zambezi, Mozambique (2008) and Zambia (2009).

To this end, different methods and approaches were proposed to flood mapping using satellite imagery:

- multi-temporal technique (http://earth.esa.int/ew/floods);
- threshold segmentation [Cunjian et al., 2001];
- statistical active contour model [Horritt, 1999];
- edge-detection techniques [Niedermeier et al., 2000];
- analysis of time-series of SAR images [Martinez and Le Toan, 2007].

The following shortcomings of the existing approaches can be identified: manual threshold selection and parameters identification; statistical models require a priori knowledge of image statistical properties; application of complex models for noise (speckle) reduction; no spatial neighbourhood between pixel is considered. More detailed description of the existing techniques is given [Kussul et al., 2008a].

Data set description. We applied our approach to the processing of remote-sensing data acquired from different satellite SAR instruments for different flood events:

- ERS-2/SAR: flood on Tisza river (Ukraine), 2001;
- ENVISAT/ASAR Wide Swath Mode (WSM): river Huaihe, China, 2007; river Zambezi, Mozambique, 2008; river Mekong, Thailand and Laos, 2008; river Koshi, India and Nepal, 2008; Ha Noi City, Vietnam, 2008; river Zambezi, Zambia, 2009;
- RADARSAT-1: river Huaihe, China, 2007;
- RADARSAT-2: river Norman, Queensland, Australia, 2009 (see Fig. 2).

Data from European satellites (ERS-2 and ENVISAT) were provided from the ESA Category-1 project "Wide Area Grid Testbed for Flood Monitoring using Spaceborne SAR and Optical Data" (№4181). Data from RADARSAT-1 satellite were provided from the Center of Earth Observation and Digital Earth (China). RADARSAT-2 data were provided by the Canadian Space Agency (CSA) within the GEOSS Architecture Implementation Pilot Phase 2 (AIP-2, http://www.ogcnetwork.net/AIpilot).

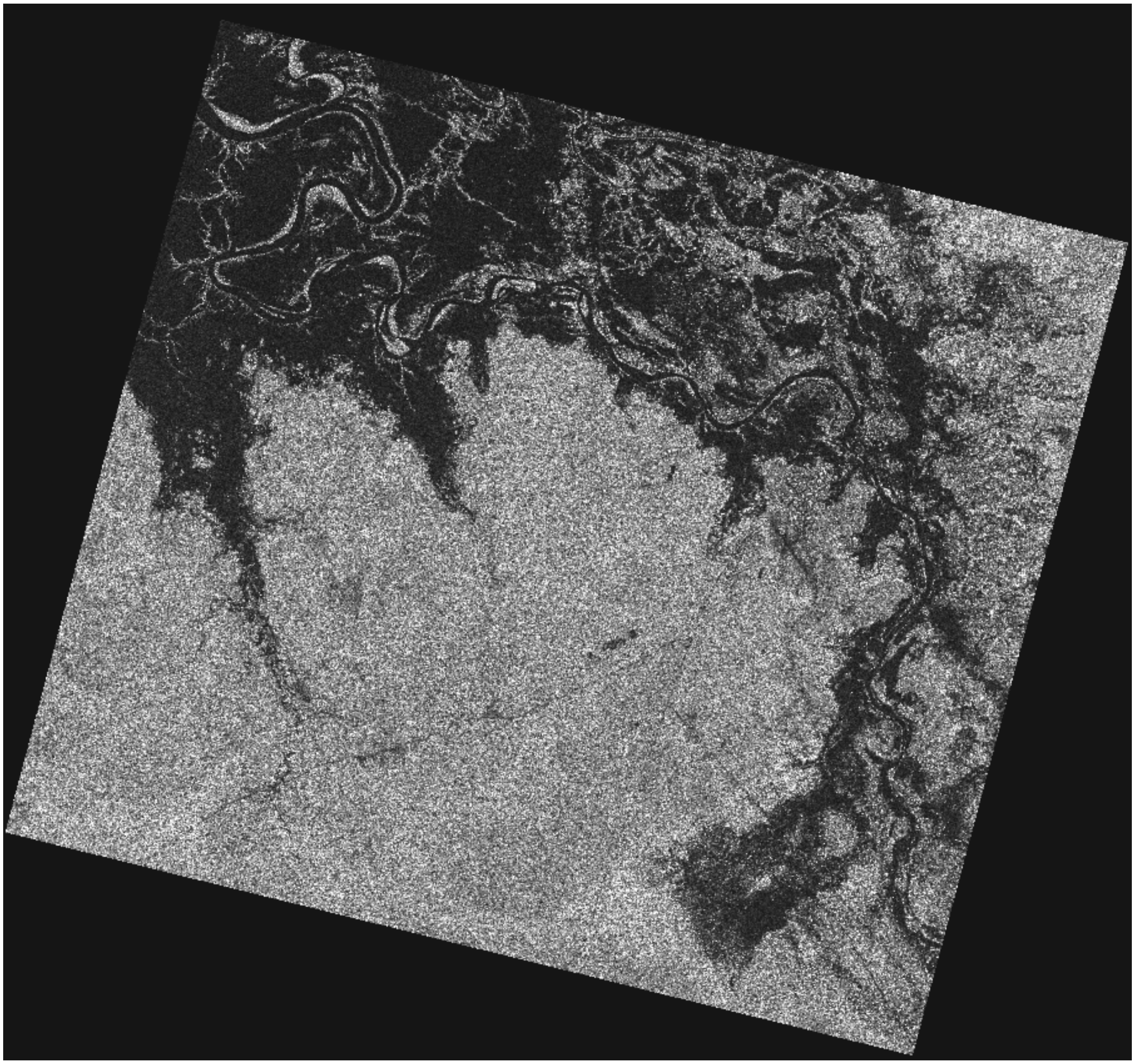


Figure 2. SAR image acquired from RADARSAT-2 satellite (date of acquisition 14.02.2009) during the flood on the river Norman, Australia (RADARSAT-2 Data and Products © MacDONALD, DETTWILER AND ASSOCIATES LTD. 2009 – All Rights Reserved. RADARSAT is an official mark of the Canadian Space Agency)

A pixel size and ground resolution of ERS-2 imagery (in ENVISAT format, SLC — Single Look Complex) were 4 m and 8 m, respectively; for ENVISAT imagery - 75 m and 150 m; and for RADARSAT-1 imagery - 12.5 m and 25 m; for RADARSAT-2 imagery – 3 m both. We used auxiliary data to derive information on water bodies (Landsat-7/ETM+, European Corine Land Cover CLC 2000) and topography (SRTM DEM v.3).

Neural network is built for each SAR instrument separately. In order to train and test neural networks, we manually selected the ground-truth pixels with the use of auxiliary data sets that correspond to both territories with the presence of water (we denote them as belonging to a class “Water”) and without water (class “No water”). For ENVISAT/ASAR instrument, data from Chinese flood event were used to construct and calibrate the neural network. This neural network, then, was used to produce flood maps for other flood events. Collected ground-truth data were randomly divided into the training set (which constituted 75% of total amount) and the testing set (25%). Data from the training set were used to train the neural networks, and data from the testing set were used to verify the generalization ability of the neural networks, i.e. the ability to operate on independent, previously unseen data sets [Haykin, 1999].

Methodology description. Our flood mapping workflow with input and output data is shown in Fig. 3 [Kussul et al., 2008a].

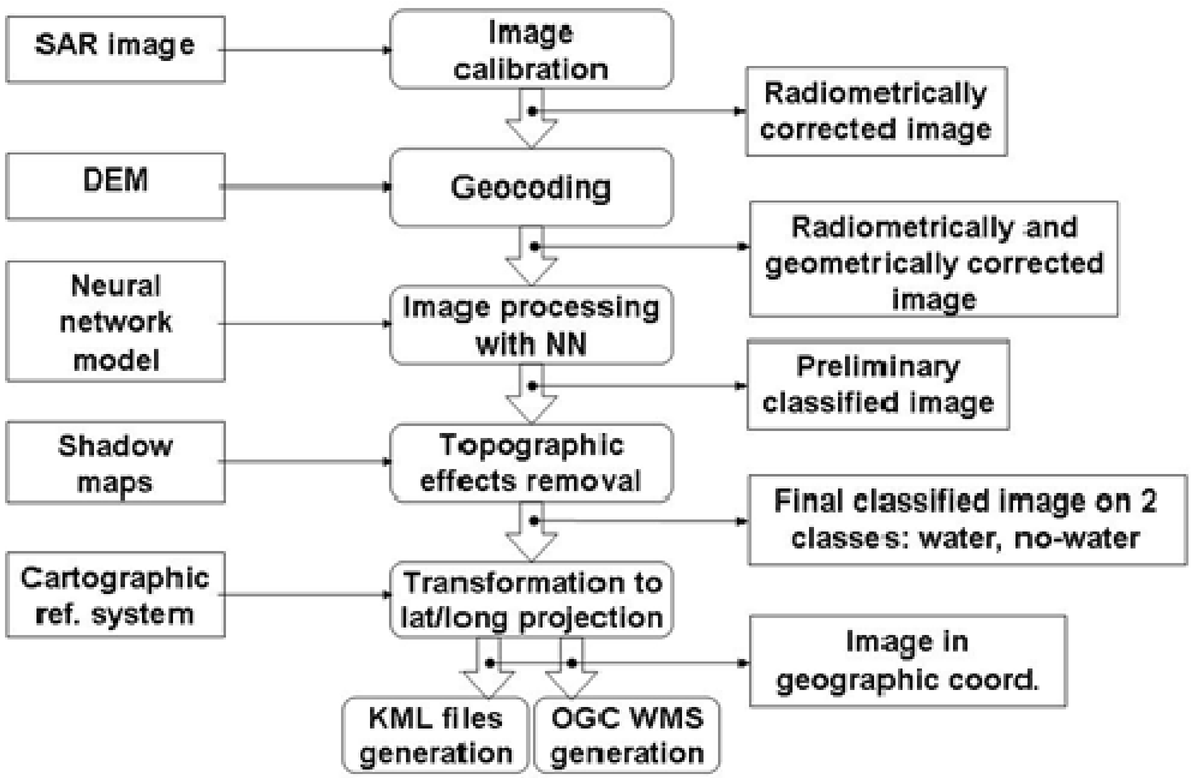


Figure 3. Flood mapping from SAR satellite imagery: workflow

SOM is a type of artificial neural network that is trained using unsupervised learning to produce a low-dimensional (typically two dimensional), discretised representation of the input space of the training samples, called a map [Kohonen, 1995; Haykin, 1999]. The map seeks to preserve the topological properties of the input space. SOM is formed of the neurons located on a regular, usually 1- or 2-dimensional grid. Neurons compete with each other in order to pass to the excited state. The output of the map is a, so called, neuron-winner or best-matching unit (BMU) whose weight vector has the greatest similarity with the input sample x.

The network is trained in the following way: weight vectors $\mathbf{w}_j$ from the topological neighbourhood of BMU vector i are updated according to [Kohonen, 1995; Haykin, 1999]

$$i(\mathbf{x}) = \arg\min_{j=\overline{1,L}} \left\| \mathbf{x} - \mathbf{w}_j \right\|,$$

$$\mathbf{w}_j(n+1) = \mathbf{w}_j(n) + \eta(n) h_{j,i(\mathbf{x})}(n)(\mathbf{x} - \mathbf{w}_j(n)),\ j = \overline{1,L} \tag{1}$$

where η is learning rate (see Eq. 3), $h_{j,i(\mathbf{x})}(n)$ is a neighbourhood kernel around the winner unit *i*, x is an input vector, $\|\bullet\|$ means Euclidean metric, *L* is a number of neurons in the output grid, *n* denotes a number of iteration in the learning phase.

The neighbourhood kernel function $h_{j,i(\mathbf{x})}(n)$ is taken to be the Gaussian

$$h_{j,i(\mathbf{x})}(n) = \exp\left(-\frac{\left\| r_j - r_{i(\mathbf{x})} \right\|}{2\sigma^2(n)} \right) \tag{2}$$

where $r_j, r_{i(\mathbf{x})}$ are the vectorial locations in the display grid of the SOM, $\sigma(n)$ corresponds to the width of the neighborhood function, which is decreasing monotonically with the regression steps.

For learning rate we used the following expression:

$$\eta(n) = \eta_0 \cdot e^{-\frac{n}{\tau}}, \eta_0 = 0.1 \tag{3}$$

where τ is a constant. The initial value of 0.1 for learning rate was found experimentally.

Kohonen’s maps are widely applied to the image processing, in particular image segmentation and classification [Kohonen, 1995; Haykin, 1999]. Prior neural network training, we need to select image features that will be give to the input of neural network. For this purpose, one can choose original pixel values, various filters, Fourier transformation etc. In our approach we used a moving window with backscatter coefficient values for ERS-2 and ENVISAT images and digital numbers (DNs) for RADARSAT-1/2 image as inputs to neural network. The output of neural network, i.e. neuron-winner, corresponds to the central pixel of moving window. In order to choose appropriate size of the moving window for each satellite sensor, we ran experiments for the following windows size: 3-by-3, 5-by-5, 7-by-7, 9-by-9 and 11-by-11.

We, first, used SOM to segment each SAR image where each pixel of the output image was assigned a number of the neuron in the map. Then, we used pixels from the training set to assign each neuron one of two classes (“Water” or “No water”) using the following rule. For each neuron, we calculated a number of pixels from the training set that activated this neuron. If maximum number of these pixels belonged to class “Water”, then this neuron was assigned “Water” class. If maximum number of these pixels belonged to class “No water”, then this neuron was assigned “No water” class. If neuron was activated by neither of the training pixels, then it was assigned “No data” class.

Results of image processing. In order to choose the best neural network architecture, we ran experiments for each image varying the following parameters: (i) size of the moving window for images that define the number of neurons in the input layer of the neural network; (ii) number of neurons in the output layer, i.e. the sizes of 2-dimensional output grid. Other parameters that were used during the image processing are as follows:

- neighbourhood topology is hexagonal;
- neighbourhood kernel around the winner unit is the Gaussian function (see Eq. 2);
- initial learning rate is set to 0.1;
- number of the training epochs is equal to 20.

The initial values for the weight vectors are selected as a regular array of vectorial values that lie on the subspace spanned by the eigenvectors corresponding to the two largest principal components of the input data [Kohonen, 1995].

We applied our approach to determine flood areas from SAR images acquired by the following instruments: ERS-2/SAR, ENVISAT/ASAR and RADARSAT-1. Classification rates for these sensors using independent testing data sets were 85.40%, 98.52% and 95.99%, respectively.

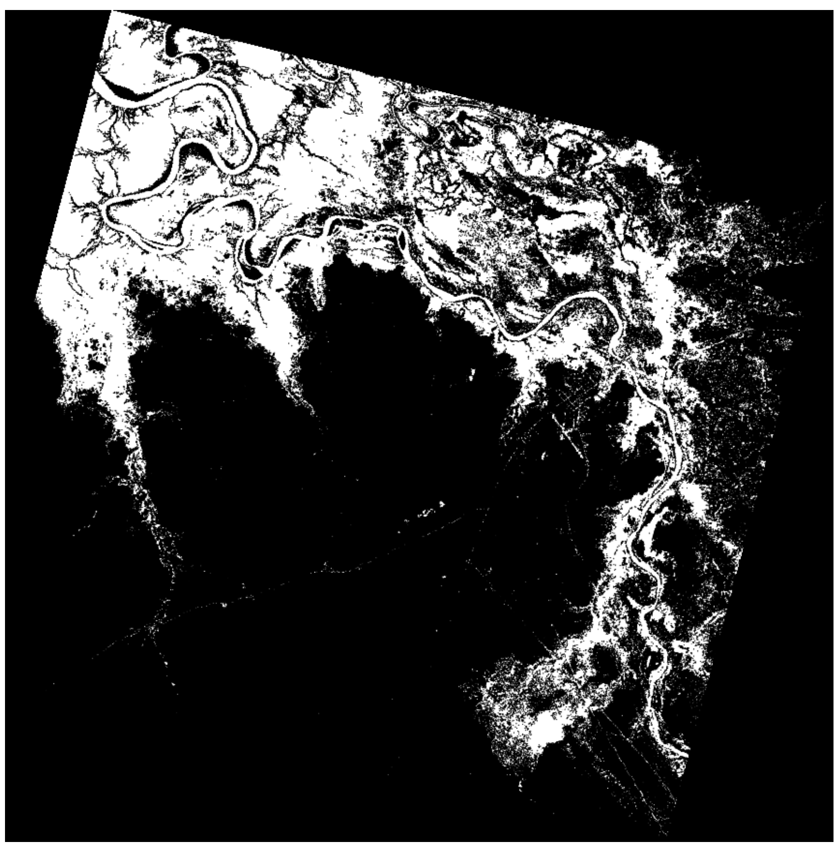


Figure 4. The resulting flood extent shown with white colour for the river Norman, Australia (© Space Research Institute NASU-NSAU 2009; RADARSAT-2 Data and Products © MacDONALD, DETTWILER AND ASSOCIATES LTD. 2009 – All Rights Reserved. RADARSAT is an official mark of the Canadian Space Agency)

For the images with higher spatial resolution (i.e. ERS-2 and RADARSAT-1), the best results were achieved for larger moving window 7-by-7. In turn, for the ENVISAT/ASAR WSM image, we used the moving window of smaller size 3-by-3. The use of higher dimension of input window for the ENVISAT image led to the coarser resolution of the resulting flood extent image and reduced classification rate.

The example of resulting flood extent map derived from RADARSAT-2 data acquired for the river Norman, Australia (see Fig. 2) is shown in Fig. 4.

Implementation. We developed a parallel version of our method and deployed it at the Grid infrastructure. Parallelization of the image processing is performed in the following way: SAR image is split into the uniform parts that are processed on different nodes using the OpenMP Application Program Interface (www.openmp.org). The use of the Grids allowed us to considerably reduce the time required for image processing. In particular, it took approximately 30 min to process a single SAR image on a single workstation. The use of Grid computing resources allowed us to reduce the time to less than 1 min.

Vegetation State Estimation. Estimation of vegetation state from satellite data has proved to be very helpful for agriculture monitoring, climate modelling, natural disasters management [Liang, 2008]. Parameters that can be estimated using optical data include Leaf Area Index (LAI), Fraction of Photosynthetic Active Radiation (FPAR), leaf pigment concentration, water concentration. Here, we will focus on plant moisture estimation from satellite data. This is very important for drought monitoring that becomes one of the major disasters in agricultural countries like Ukraine. For example, drought in Ukraine in 2007 resulted in $100 millions losses.

Water shortage in plants and plant stress in general can be detected by optical satellite data. Vegetation moisture determination is possible mainly due to significant differences in reflectance in Shortwave Infrared band of electromagnetic spectrum (SWIR) of vegetation under water stress and under normal conditions. However, in solar optical domain vegetation reflectance is controlled not only by moisture but by several other factors: leaf structure, pigment concentration, LAI, soil reflectance [Liang, 2004]. Due to this plant moisture estimation is far from trivial.

This estimation task is a massive parallel problem since estimation has to be performed on the per pixel basis. And, even if the problem is not computationally complex for a single pixel, it has to be solved for each pixel of the satellite imagery. For current moderate resolution sensors such as MODIS 1 million pixels has to be processed per day, and new satellite systems such as RapidEye will deliver billions pixels per day. Nevertheless, this problem is highly parallelizable and, thus, is a good candidate to be executed in a Grid environment.

Earlier approaches to vegetation moisture estimation were based on so-called Vegetation Indexes [Ceccato et al., 2002; Gao, 1996]. Index is a simple combination of reflectance in different bands of satellite image which has increased sensitivity to target variable like moisture content and low sensitivity to other factors. For example, one of the popular indexes is a Normalized Difference Water Index (NDWI):

$$NDWI = \frac{\rho_{0,8} - \rho_{1,6}}{\rho_{0,8} + \rho_{1,6}} \quad (4)$$

where $\rho_{0,8}$ and $\rho_{1,6}$ are reflectance value in Near Infrared band (NIR) and SWIR band.

Vegetation Indexes uses only a limited number of spectral bands (2-3) while modern sensors like MODIS, MERIS have 7-15 bands. Also, indexes remain only indirect measures of target variables, and additional regressions have to be used to estimate it. Usually, such regressions require additional calibration using local data which further complicates utilization of Vegetation Indexes. That is why, at present, the modern way to estimate vegetation parameters is based on more sophisticated approach – physical modelling of satellite signal using canopy radiative transfer models [Liang, 2004].

Problem statement. Under modelling approach the estimation problem is considered as inverse to the problem of simulation of satellite signal. For the latter task the wide range of models exists [Liang, 2004], among which several models (like PROSPECT [Feret et al., 2008] and SAIL [Verhoef et al., 2007]) are widely used in remote sensing. For our purpose we will formulate radiative transfer model as a mapping $h:\mathbf{R}^{n_x}\to\mathbf{R}^{n_d}$ that maps state of vegetation $x\in X\subset\mathbf{R}^{n_x}$ into reflectance in different bands $h(x)\in D\subset\mathbf{R}^{n_d}$:

$$d=h(x)+h(x)\varepsilon \qquad (5)$$

where d is measurement vector and ε is noise vector. This problem is characterized by multiplicative noise [Bacour et al., 2006].

For instance, for PROSPECT leaf radiative transfer model the dimension of x is four $x=(N,C_{ab},C_w,C_m)^T$, where N — leaf structure parameter, while C_{ab} , C_w , C_m — concentration of chlorophyll, water and dry matter. Dimension of model output vector $h(x)$ is 2100, however for remote sensing purposes model output has to be aggregated to be comparable with current multispectral sensors. So usually the dimension of observation vector d is much smaller, for instance for MODIS sensor it will be 7.

In this paper the Bayesian approach to inverse problems is considered [Tarantola, 2005]. Within this approach uncertainty in a priory estimate of state vector x and in process of measurement of reflectance vector $h(x)$ has probabilistic nature. Let $\mathbf{x}$, $\mathbf{d}$, $\boldsymbol{\varepsilon}$ — random vectors of a priory estimate of model input, observations and noise in observations, $p(x)$, $p(d)$ and $p(\varepsilon)$ — densities of probability distributions of these vectors. It is assumed that random vectors $\mathbf{x}$ and $\boldsymbol{\varepsilon}$ are independent, while densities $p(x)$, $p(\varepsilon)$ and function h is such, that random vectors $\mathbf{x}$ and $\mathbf{d}$ have common density $p(x,d)$ and components of these vectors have variance.

The solution of inverse problem is conditional density of model input $\mathbf{x}$ with respect of known value of observations vector $\mathbf{d}$ [Tarantola, 2005]:

$$p(x\,|\,d)\propto p(d\,|\,x)p(x),\quad x\in\mathbf{R}^{n_x},d\in\mathbf{R}^{n_d} \qquad (6)$$

However, for practical purposes we have to estimate some properties of above conditional density, like mean, standard deviation, median, most probable value etc.

Neural network method to solve inverse problem. There are several methods to estimate properties of (6): Monte-Carlo [Qingyuan et al., 2005], variational [Bacour et al., 2002], lookup tables [Combal et al., 2002] and neural networks [Bacour et al., 2006]. However, in recent years neural networks gain a lot of attention due to their ability to approximate arbitrary continuous function and computational efficiency [Haykin, 1999].

To solve inverse problem (6) within traditional neural network approach the approximation $f: D \to X$ of inverse mapping to $h: X \to D$ is constructed using neural network, for instance Multilayer Perceptron (MLP). This is performed through minimization of quadratic functional:

$$J(w) = \frac{1}{2}\sum_i \left\| x_i - f(d_i, w) \right\|^2 \tag{7}$$

where function $f(\cdot, w)$ is defined by neural network with weight coefficients w, $\{(d_i, x_i), i = \overline{1,n}\}$ is learning sample set created via sampling from density $p(x,d)$.

It can be shown (see for instance [Bishop, 1996; Kravchenko, 2009]) that given sufficient number of learning samples neural network with quadratic error criteria will approximate conditional mean $\mathrm{E}[\mathbf{x} \mid \mathbf{d} = d] = \int xp(x \mid d)dd$ of network output x given input d. So in the framework traditional neural network approach we can obtain only point estimate of parameters. To overcome this deficiency of traditional neural networks for inverse problem solving we propose to apply neural networks with nonquadratic error criteria, such as Mixture Density Networks (MDN) [Bishop, 1996]. Such networks allow modelling of conditional density $p(x \mid d)$ as a mixture of Gaussian densities.

$$p_{MDN}(x \mid d,w) = \sum_{l=1}^{L} \alpha_l(d,w) \cdot \phi\left(x; m_l(d,w), \sigma_l(d,w)\right) \tag{8}$$

where $\phi(x;m,\sigma) = \frac{1}{\left(\sqrt{2\pi}\sigma\right)^{n_x}} \exp\left(-\frac{\left\|x-m\right\|^2}{2\sigma^2}\right)$ — Gaussian density with mean m and diagonal covariance matrix $\sigma^2 \mathrm{I}$, α_l — mixture coefficients ($\sum_l \alpha_l = 1$), L — number of elements of mixture. Functions $\alpha_l(d,w)$, $m_l(d,w)$ and $\sigma_l(d,w)$ are constructed using MLP with modified output layer. MDN is learned through minimising the following error criteria:

$$J(w) = \frac{1}{n}\sum_{i=1}^{n} -\ln p_{MDN}(x_i \mid d_i, w) \tag{9}$$

Unlike MLP, MDN with even one Gaussian component in mixture can approximate both conditional mean and variance of $p(x \mid d)$ [Kravchenko, 2009].

Numerical experiment with PROSPECT model.

Here we will demonstrate use of MDN to solve inverse problem of leaf moisture estimation. To formulate forward problem we will use PROSPECT leaf radiative transfer model. In this case x vector consists of 4 parameters: $x = \left(N, C_{ab}, C_w, C_m\right)^T$, while observation vector d consists of seven leaf reflectances in MODIS-like spectral bands. To pose inverse problem we will assume uniform a priory density $p(x)$ and independent Gaussian noise model for $\boldsymbol{\varepsilon}$ (5% standard deviation). To estimate plant moisture we will use MDN with 7 neurons in input layer, 5 neurons in hidden layer and one-dimensional mixture containing one Gaussian component. This network is used to estimate mean and variance of conditional density $p(C_w \mid d)$. Increasing number of mixture's components or number of neurons in hidden layer does not improve the quality of solution in this problem.

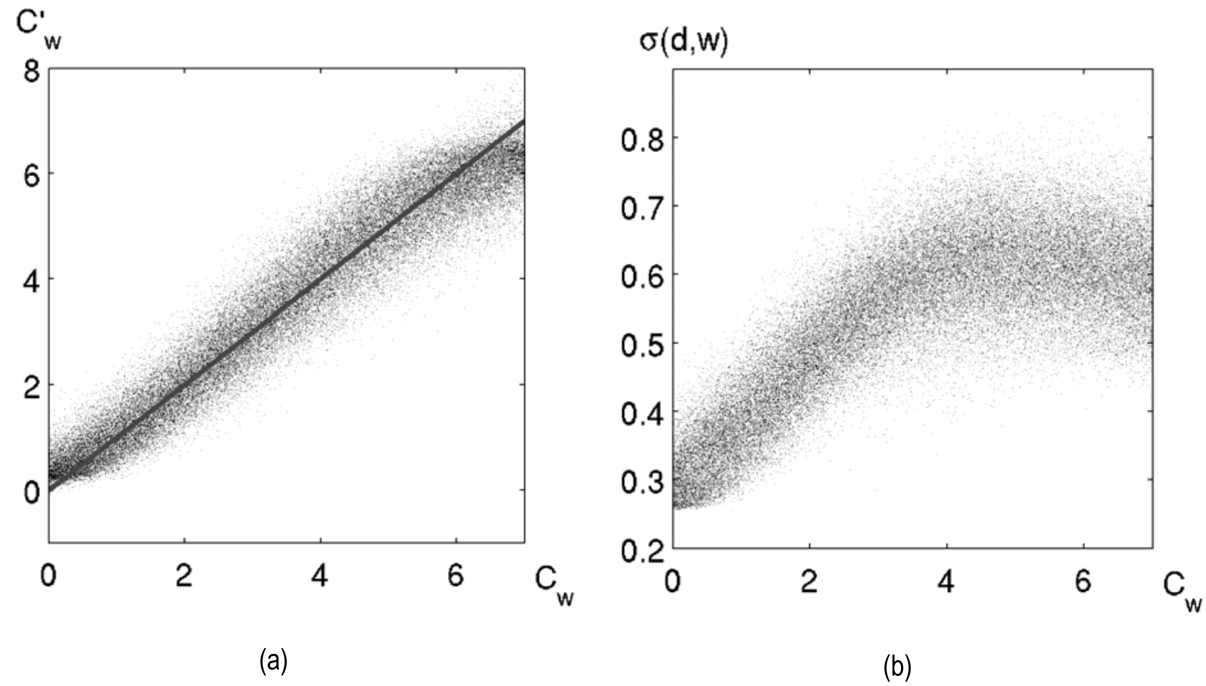
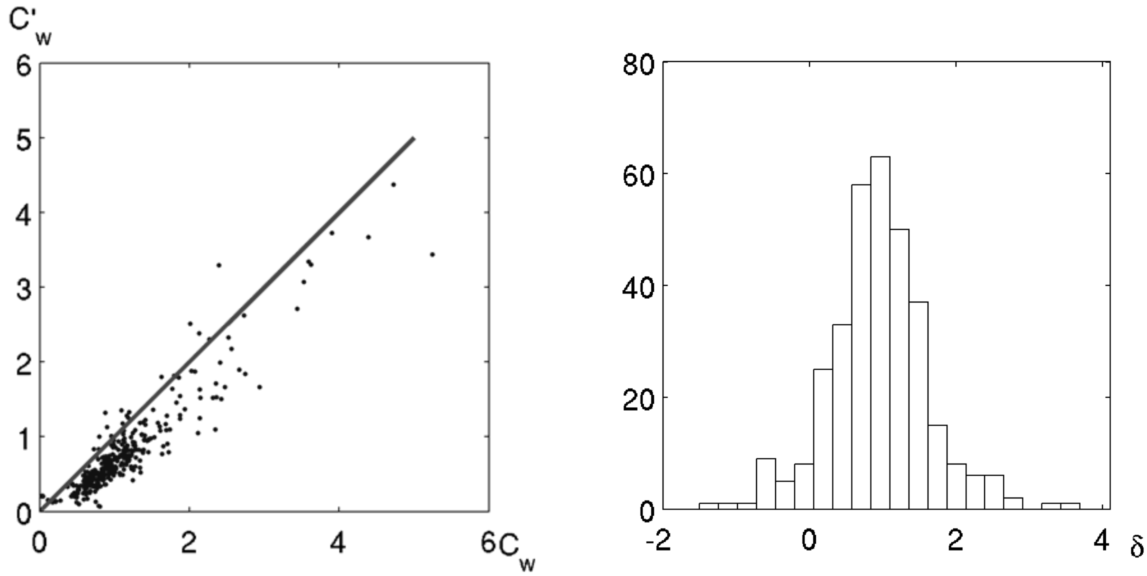


Figure 5. a — scatter plot of estimated leaf moisture $C_w^{'}$ and true C_w; b — dependency of estimate of standard deviation of leaf moisture $\sigma(d,w)$ w.r.t. real leaf moisture C_w

Scatter plot of conditional mean of leaf moisture $C_w^{'} = m_1(d_i, w)$ estimated by MDN given observation d_i and true value C_w is shown on fig. 5a (identical dependency is shown by strait line), while dependency of estimate of standard deviation of leaf moisture $\sigma(d_i, w)$ given observation d_i with respect to true value C_w is shown in Fig. 5b. Standard deviation is increased with increase of moisture C_w and stabilized for large C_w (4-7 cg/cm^2). This is in accordance with the fact that sensitivity of SWIR reflectance is decreased for large leaf moisture values.

Validation results. To validate our algorithm we used LOPEX leaf optical properties database (Leaf Optical Properties EXperiment). This database contains over 1250 plant reflectance spectra. For validation purpose 330 fresh leaf spectra of 66 plant species at different moisture level were used. Spectra were aggregated using MODIS band relative spectral response functions. Fig. 6a shows the scatter plot of estimated leaf moisture ($C_w^{'}$) and observed (C_w), while fig. 6b shows the histogram of moisture estimation error normalized by estimate of standard deviation

$\delta = \left(C_w^{'} - C_w\right) / \sigma(d_i, w)$. Most of the departures (90%) are located in $[-2;2]$ interval (in $\pm 2\sigma$ interval) that confirms adequacy of standard deviation estimates using MDN.



(a) (b)

Figure 6. a — scatter plot of estimated leaf moisture $C_w^{'}$ and true C_w; b — histogram of normalized errors δ

Levels of Integration: Main Problems and Possible Solutions

Modern tendencies of globalization and development of the “system of systems” GEOSS lead to the need of integration of heterogeneous satellite-based monitoring systems. Integration can be done at different levels: (i) data exchange level, (ii) task management level. Data exchange is supposed to provide infrastructure for sharing data and products. This infrastructure enables data integration where different entities provide various kinds of data to support joint solution of complex problems (Fig. 7). Task management level envisages running applications at distributed computational resources provided by different entities (Fig. 8). Since many of the existing satellite monitoring system rely on Grid technologies appropriate approaches and technologies should be evaluated and developed to enable Grid system integration (so called InterGrid).

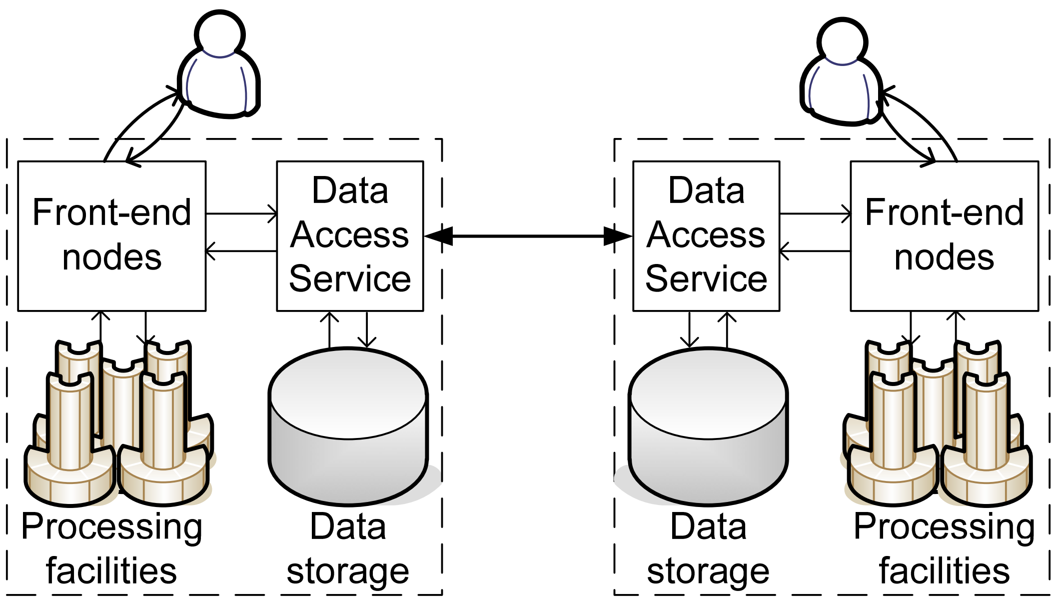


Figure 7. Data integration level

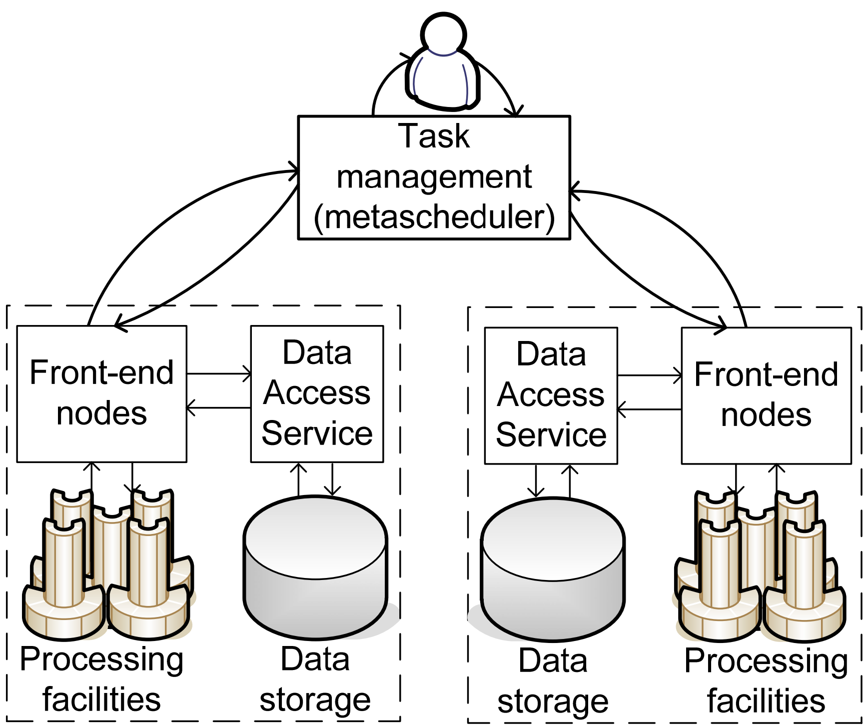


Figure 8. Task management level

This section highlights main challenges and possible solutions for satellite monitoring systems integration at both levels, and provides the case-studies for both cases.

Integration at data exchange level could be done by using common standards for EO data exchange, common user interfaces, and common data and metadata catalogues. Considering the task management level, the following problems additionally should be tackled: the use of joint computational infrastructure; development of jobs submission and scheduling algorithms; load monitoring enabling; security policy enforcement.

Data exchange level. At present the most appropriate standards for data integration is Open Geospatial Community (OGC) standards. Data visualization issues can be solved by using the following set of standards: WMS (Web Map Service), SLD (Style Layer Descriptors) and WMC (Web Map Context). OGC's WFS (Web Feature Service) and WCS (Web Coverage Service) standards provide uniform ways for data delivery. In order to provide interoperability at the level of catalogues CSW (Catalogue for Web) standard can be applied.

Since data are stored at geographically distributed sites there can be issues regarding optimization of visualization schemes. In general, there are two possible ways for distributed data visualization: centralized visualization scheme and distributed visualization scheme. Advantages and faults of each scheme were described in [Shelestov et al., 2008].

Task management level. In this subsection we present main issues and possible solutions for Grid-system integration. Main prerequisite of such kind of integration is certificates trust. It could be done, for example, through EGEE infrastructure that nowadays brings together the resources of more than 70 countries. Another problems concerned with different Grid systems integration are as follows: enabling data transfers and high-level access to geospatial data; development of common catalogues; enabling jobs submission and monitoring; enabling information exchange.

Data transfer. GridFTP is an appropriate and reliable solution for data transfer. The only limitation is the requirement of transparent LAN (local area network) infrastructure.

Access to geospatial data. High-level access to geospatial data can be organised in two possible ways: using pure WSRF services or using OGSA-DAI container. Each of this approach has its own advantages and weaknesses. Basic functionality for WSRF-based services can be easily implemented (with proper tools), packed and deployed. But advanced functionality such as security delegation, third-party transfers, indexing should be implemented by hands. WSRF-based services can also pose some difficulties if we need to integrate them with other data-oriented software.

OGSA-DAI framework provides uniform interfaces to heterogeneous data. This framework makes possible to create high-level interfaces to data abstracting hiding details of data formats and representation schemas. Most of problems in OGSA-DAI are handled automatically, e.g. delegation, reliable transfer, data flow between different sources and sinks. OGSA-DAI containers are easily extendable and embeddable. But comparing to WSRF basic functionality implementation of OGSA-DAI extensions is more difficult. Moreover, OGSA-DAI require preliminary deployment of additional software components.

Task management. There are two possible approaches for task management. One of them is to use Grid portal (Fig. 9) supporting different middleware platforms, such as GT4, gLite, etc. Grid portal is an integrated platform to end-users that enables access to Grid services and resources via standard Web browser. Grid portal solution is easy to deploy and maintain, but it doesn't provide application interface and scheduling capabilities.

Another approach is to develop high-level Grid scheduler (Fig. 10) that will support different middleware by providing some standard interfaces. Such metascheduler interacts with low-level schedulers (used in different Grid systems) enabling in such way system interoperability. Metascheduler approach is much more difficult to maintain comparing to portals; however, it provides API with advanced scheduling and load-balancing capabilities. At present, the most comprehensive implementation for the metascheduler is a GridWay system. The GridWay metascheduler is compatibility with both Globus and gLite middlewares. Starting from Globus Toolkit v4.0.5 GridWay become standard part of its distribution. GridWay system provides comprehensive documentation for both users and developers that is an important point for implementing new features.

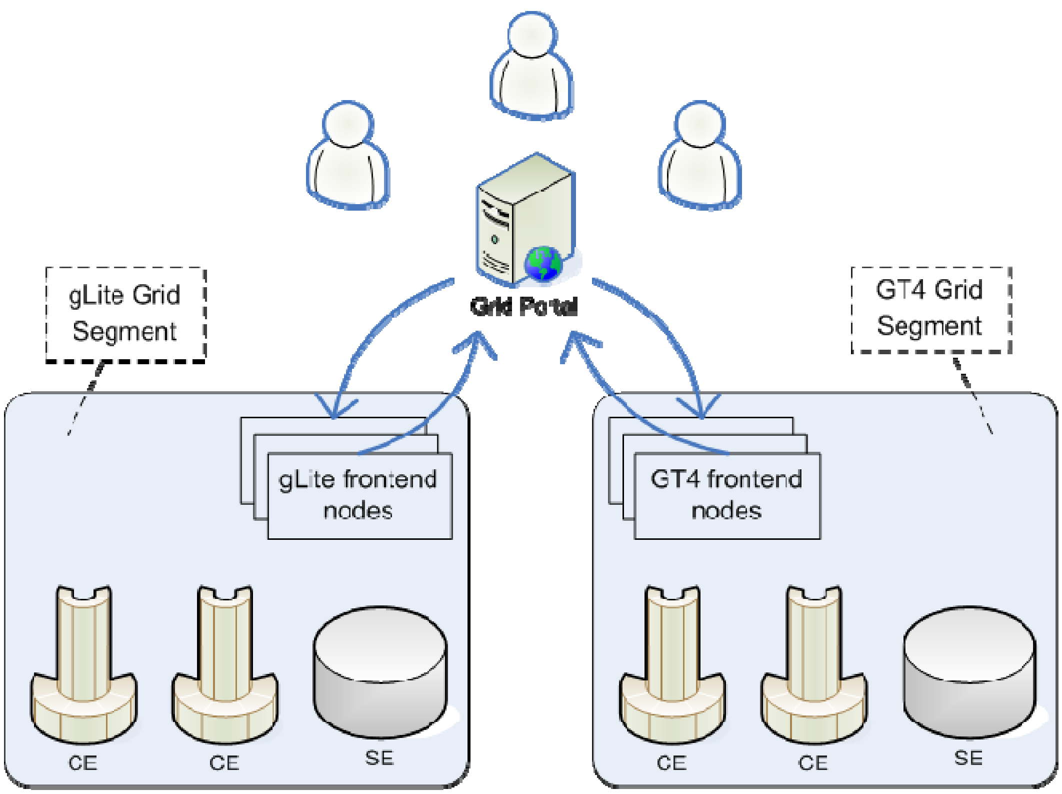


Figure 9. Portal approach to Grid system integration

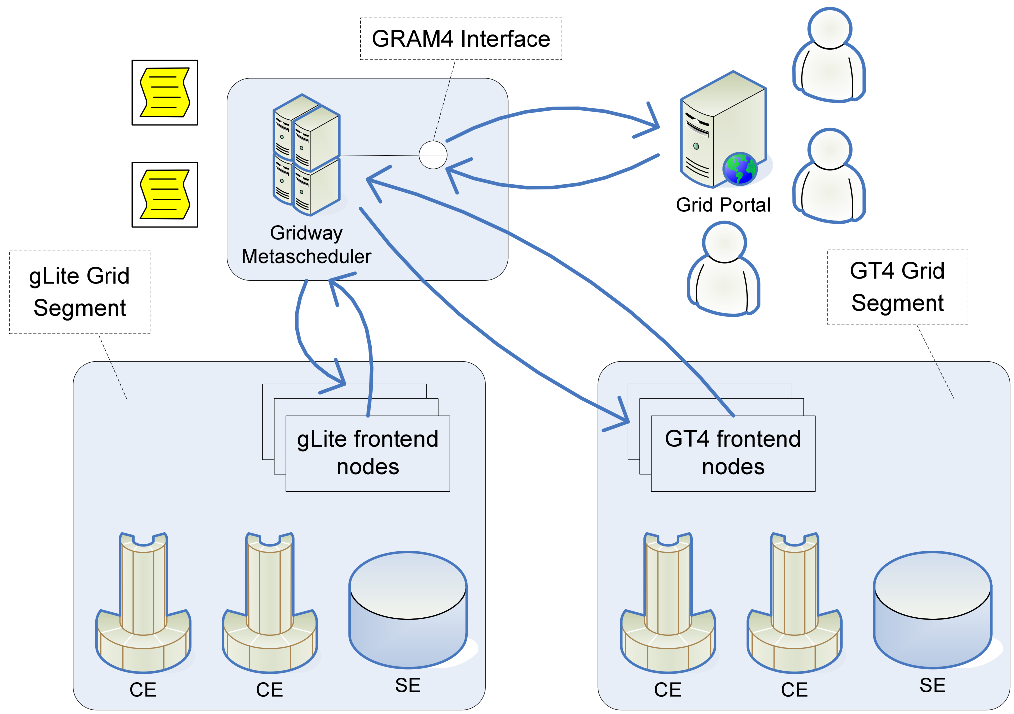


Figure 10. Metascheduler approach

In the next section we show the examples of application of described approaches to integration of satellite monitoring systems and development of InterGrid environment.

Implementation: Lessons Learned

Integration of satellite monitoring systems. The first case-study refers to the integration of satellite monitoring systems of NSAU (Ukraine) and IKI RAN (Russia). The overall architecture for integration of data provided by two organizations is depicted in Fig. 11. The proposed approach is applied for the solution of problems for agriculture resources monitoring and crop yield prediction. Within integration NSAU provides WMS interfaces to NWP modelling data (using WRF model) [Kussul et al., 2008b], in-situ observations from meteorological ground stations in Ukraine, and land parameters (such as temperature, vegetation indices, soil moisture) derived from satellite observations from MODIS instrument onboard Terra satellite. IKI RAN provides WMS interfaces to operational land and disaster monitoring system. Both NSAU and IKI RAN provides user Web-interfaces to monitoring systems that support OGC WMS standards.

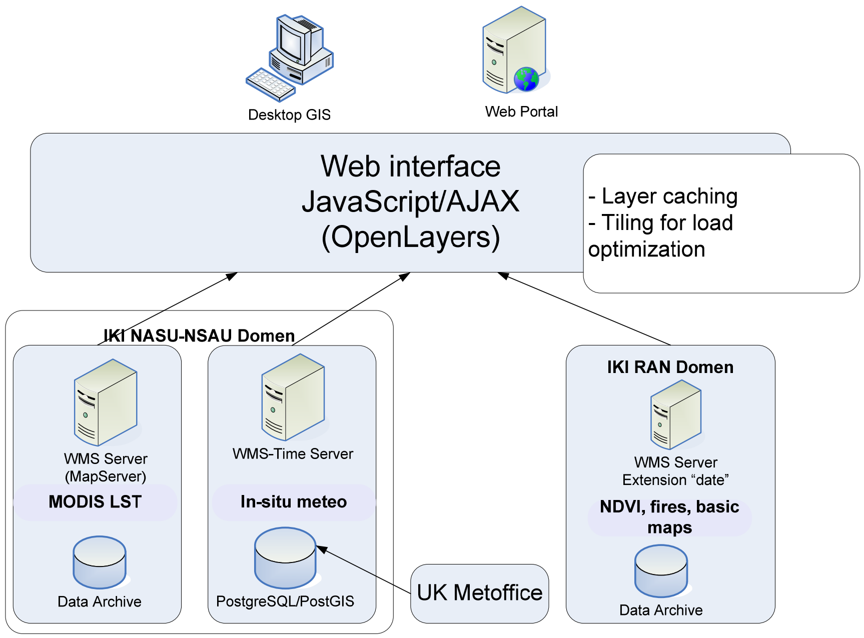


Figure 11. Architecture of satellite monitoring system integration

In order to provide user interface that will enable visualization of data from multiple sources we use open-source OpenLayers framework (http://www.openlayers.org). OpenLayers is "thick client" software based on JavaScript/AJAX and fully operational on client side. Main OpenLayers features also include: support for several WMS servers, support for different OGC standards (WMS, WFS), cache and tiling support to optimize visualization, support for of both raster and vector data. The provided data and products are accessible via Internet http://land.ikd.kiev.ua. The example of OpenLayers visualization of data from multiple sources is depicted in Fig. 12.

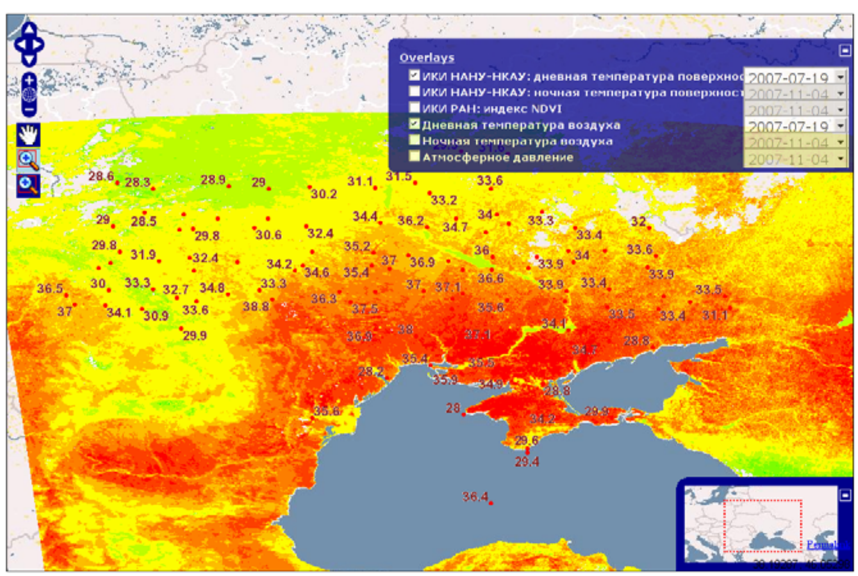


Figure 12. OpenLayers interface to multiple data

InterGrid testbed development. The second case-study refers to the development of InterGrid for environmental and natural disaster monitoring. InterGrid integrates Ukrainian Academician Grid (with Satellite data processing Grid segment) and CEODE Grid (Chinese Academy of Sciences) and is considered as a testbed for Wide Area Grid (WAG) implementation—a project initiated within CEOS Working Group on Information Systems and Services (WGISS).

The important application that is being solved within InterGrid environment is flood monitoring and prediction. This task requires adaptation and tuning of existing hydrological and hydraulic models for corresponding territories and the use of heterogeneous data stored at multiple sites. Flood monitoring and prediction requires the use of the following data sets: NWP modelling data (provided by Satellite data processing Grid segment), SAR imagery from Envisat/ASAR and ERS-2/SAR satellites (provided by ESA), products derived from optical and microwave satellite data such as soil moisture, precipitation, flood extent etc., in-situ observations from meteorological ground stations and digital elevation model (DEM). The process of model adaptation can be viewed as a complex workflow and requires the solution of optimization problems (so called parametric study). Satellite data processing and products generation tasks also represent complex workflow and require intensive computations. All these factors lead to the need of using computational and informational resources of different organizations and their resources into joint InterGrid infrastructure. The architecture of proposed InterGrid is depicted in Fig. 13.

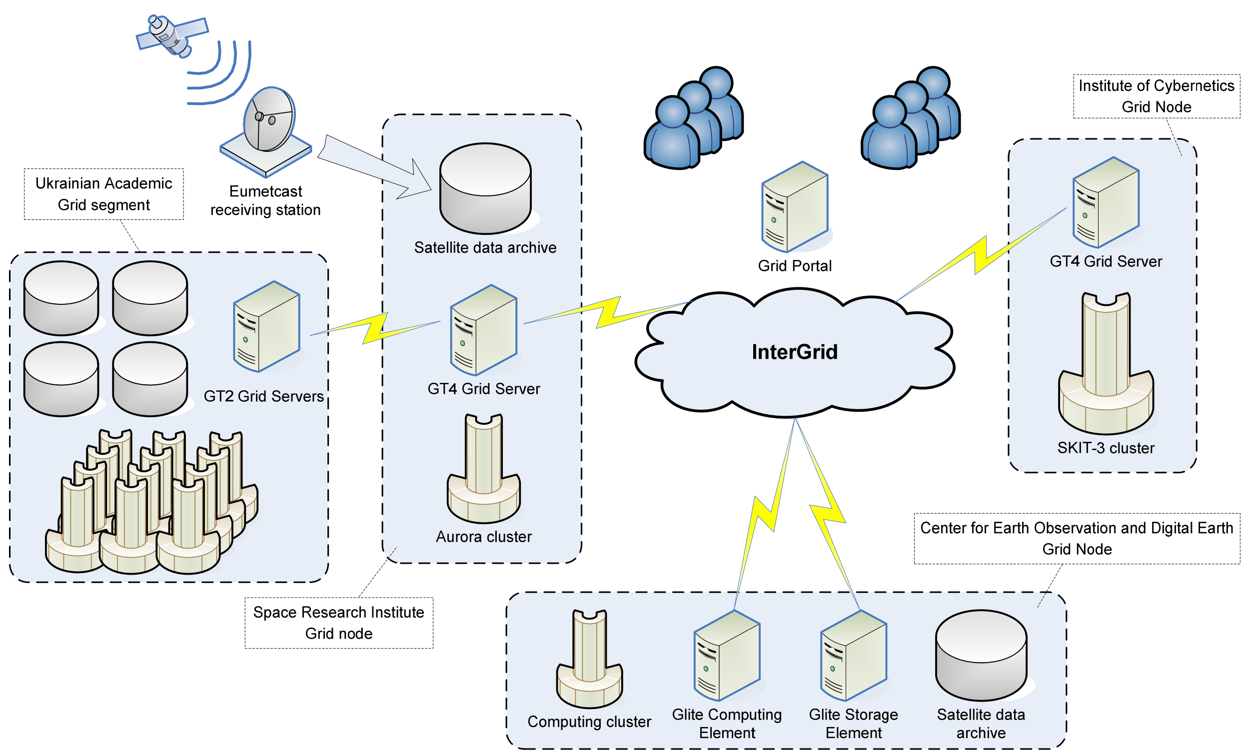


Figure 13. InterGrid architecture

GridFTP was chosen to provide data transfer between Grid systems. In order to enable interoperability between different middleware (for example, Satellite data processing Grid segment is using GT4; CEODE Grid is using gLite 3.x; Ukrainian Academician Grid is based on NorduGrid) we developed Grid portal that is based on GridSphere portal framework (http:// www.gridsphere.org). The developed Grid portal allows users to transfer data between different nodes and submit jobs on computational resources of the InterGrid environment. The portal also provides facilities to monitor statistics of the resources such as CPU load, memory usage, etc. The further works on providing interoperability between different middleware are directed to the development of metascheduler using GridWay system. In the nearest future we are intended to provide integration with ESA's EO Grid-on-Demand infrastructure.

Conclusions

This paper presented different approaches to multi-source data integration for the solution of complex applied problems in the Earth Science domain. In particular, we considered two problems, flood mapping and vegetation state estimation that requires the use of heterogeneous data acquired from multiple sources: remote-sensing from space, modelling and in-situ observations. We used satellite SAR imagery and DEM to extract flood extent from satellite data. To segment and classify the imagery we used self-organising Kohonen maps that provide such useful features as effective software tool for the visualization of high-dimensional data, automatically discover of statistically salient features of pattern vectors in data set, and possibility to find clusters in training data pattern space which can be used to classify new patterns. We tested our approach for various SAR instruments and for a number of flood events covering various geographical regions. The achieved classification rate was from 85.40% to 98.52% depending on the SAR instrument used.

Another application was vegetation state estimation from satellite and modelling data. We use physical modelling of satellite signal using canopy radiative transfer models. Under this approach the estimation problem is considered as inverse to the problem of simulation of satellite signal. To solve inverse problems we apply neural networks, namely Mixture Density Networks (MDNs) that allow the modelling of conditional density as a mixture of Gaussian densities. Another useful property of MDNs is that they can approximate both conditional mean and variance in the output density. We run different numerical experiments using PROSPECT model and LOPEX leaf optical properties database. Most of the departures (90%) were located in $\pm 2\sigma$ interval that confirms adequacy of standard deviation estimates using MDNs.

Since both these applications are data- and computation-intensive, we use Grid computing technologies. In such a case computational and informational resources are geographically distributed and may belong to different organisations. For this purpose, we also investigated benefits of different approaches to the integration of satellite-based monitoring systems. We investigated two possible levels of integration, namely data level and task management level. As to data integration level, we found that integration could be provided by using existing standards for geospatial data, in particular OGC standards. We demonstrated applicability and usability of this approach to the integration of existing satellite monitoring systems of Ukraine and Russia for agriculture applications. The use of standard OGC interfaces makes it possible to standardise and facilitate the development of integrated satellite monitoring systems (based on existing systems) to exploit the synergy and acquire information of new quality. As to integration at task management level, we reviewed two solutions: portal-based and metascheduling approach. We implemented portal solution based on the GridSphere framework to the InterGrid environment that integrates several regional and national Grid systems. In order to provide advanced scheduling and load-balancing capabilities the further works will be directed to the implementation of metascheduler based on GridWay system.

Further investigations will be directed to the integration of distributed monitoring systems with Sensor Web to provide automatic delivery of data from heterogeneous sources and their processing in the Grid environment.

Acknowledgment

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