Assessment of Multi-spectral Vegetation Indices using Remote Sensing and Grid Computing

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***Abstract*—**A primary goal of many remote sensing projects is to characterize the type, size and condition of vegetation present within a region. By combining data from two or more spectral bands we obtain what is commonly known as a vegetation index (VI), which enhances the vegetation signal, while minimizing solar irradiance and soil background effects. This study addresses the computation of Normalized Difference Vegetation Index (NDVI), Ratio Vegetation Index (RVI), Enhanced Vegetation Index (EVI), Atmospherically Resistant Vegetation Index (ARVI), Normalized Difference Snow Index (NDSI) and Normalized Burn Ratio (NBR) based on satellite imagery. As the analysis is performed on large data sets, we used Grid Computing to implement a service for using on Computational Grids with a Web-based client interface, which will be greatly useful and convenient for those who are studying the growth and vigor of green vegetation by using environmental remote sensing, and have typical workstations, with no special computing and storing resources for computationally intensive satellite image processing and no license for a commercial image processing tool.

***Keywords*—**Grid Computing, Remote Sensing, Vegetation Indices

I. Introduction

GRID Computing is an emerging technology that provides access to computing power and data storage capacity distributed over the globe. Grid computing is the use of multiple computers to solve a single problem at the same time – usually a scientific problem that requires a great number of computer processing cycles or access to large amounts of data [3].

Grid computing offers the potential of virtual organizations groups of people both geographically and organizationally distributed working together on problems, sharing computers and other resources such as databases and experimental equipment. The challenge with a Grid infrastructure is to be able to dynamically locate, manage, and assure quality performance from participating systems. Grid technology has the potential to significantly impact many areas of study with heavy computational requirements, like chemistry, physics, genetics, encryption, math, modeling, animations, digital video production, image processing [6], [7], [10], [14], [15] etc.

Vegetation indices (VI) were first developed in the 1970s and have been highly successful in assessing vegetation condition, foliage, cover, penology, and processes such as evapotranspiration (ET). They are combinations of spectral measurements in different wavelengths as recorded by a radiometric sensor and aid in the analysis of multispectral image information by shrinking multidimensional data into a single value. Huete (1994) defined vegetation indices as: "dimensionless, radiometric measures usually involving a ratio and/or linear combination of the red and near-infrared (NIR) portions of the spectrum. VI's may be computed from digital counts, at satellite radiances, apparent reflectances, land-leaving radiances, or surface reflectances and require no additional ancillary information other than the measurements themselves". Vegetation indices serve as indicators of relative growth and vigor of green vegetation, and are diagnostic of various biophysical vegetation parameters.

Most of the vegetation indices ratio the reflection of light in the red and NIR sections of the spectrum to separate the landscape into water, soil, and vegetation. As ratios, they can be easily cross-calibrated across sensor systems, ensuring continuity of data sets for long-term monitoring of the land surface and climate-related processes. VI's are now indispensable tools in land cover classification, climate and land-use-change detection, drought monitoring, and habitat loss. They have been found to be related to a number of biophysical parameters of interest to many researchers, including Leaf Area Index (LAI), percent vegetation cover, green leaf biomass, fraction of absorbed photosynthetically active radiation (fAPAR), photosynthetic capacity, and carbon dioxide fluxes.

Due to satellite images large size – up to 1 GB, in order to remotely estimate the vegetation indices using satellite imagery it is desirable to distribute the processing of satellite images over a heterogeneous network of computers, where each of them contributes to a faster result according to its capabilities. In this context, Grid computing may be a solution.

In this study, we describe a service for using on Computational Grids, which addresses the computation of Normalized Difference Vegetation Index (NDVI), Normalized Difference Snow Index (NDSI) and Normalized Burn Ratio (NBR) based on satellite imagery. This service will extend the functionality of the web platform described in [5], which

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consists of already implemented Grid services that compute various environmental remote sensing algorithms applied over the Dobrogea region.

This paper is organized in 5 sections. The first section is Introduction and the second presents the Study Area and Input Data Sets. The third section shows the Methodology used in the study. Next, in section 4, we describe the service that uses the Computational Grid and the experimental results. Conclusion and further work are approached in section 5.

II. Problem Formulation

A. Study Area

Dobrogea region has been chosen for this study due to its importance in the Romanian economy. Dobrogea together with Romanian plain and South of Moldova are among the driest areas, where the crops cannot grow without irrigation systems. It is absolutely necessary to know VI as management method of the water sources for irrigation, for the design and exploitation of the irrigation systems.

Dobrogea is a region situated in the South – East of Romania, between the Black Sea and the lower Danube River (Fig.1).

Dobrogea (without the Danube Delta) is a plateau with hilly aspect. Generally, it has a temperate - continental climate. The air average temperature is slightly over 110C towards the littoral area and the Danube floodplain, and no more than 10 - 110C in the North and center.

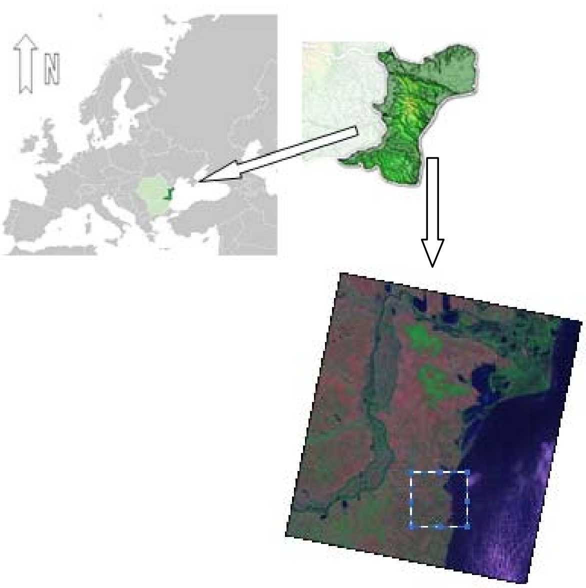

Fig. 1 Dobrogea region

B. Input Data Sets - Satellite Data

The Landsat program has been operating since 1972, allowing for uninterrupted observation of Earth throughout this period and making it an invaluable tool for longitudinal studies of environmental problems. The satellite's sunsynchronous orbit takes it over the same location on Earth every 16 days so data is never very old. This makes it ideal for mapping short-term variations in vegetation on a global scale. The variations in vegetation cover between early spring and early autumn over entire continents can be seen under cloud-free conditions, making it possible to construct monthly vegetation charts. Cumulative values of NDVI, for example, may be used to estimate crop yields and anticipate food shortages.

In this study, we used a subset of Landsat ETM+ image dated 7th June 2000. The image is in geo-tiff format and was downloaded from [9]. A radiometric calibration (atmospheric corrections) was the pre-processing step that was taken.

III. Methodology

A. Satellite Data Pre-processing

Satellite data pre-processing comprise of radiometric calibrations (atmospheric corrections) for TM/ETM+ bands 2, 3, 4, 5 and 7. It is possible to obtain the NDVI (NDSI or NBR) values from at-sensor or TOA (Top of Atmospheric) reflectivities, called as NDVITOA, but it is more accurate to atmospherically correct the TOA values in order to obtain at-surface reflectivities and, in this way, estimate NDVI values more representative of the natural surfaces, called as NDVIsurf.

In this study we applied an atmospheric correction based on image data, developed by [10], its main advantage being that the data necessary in order to carry out the atmospheric correction are obtained from the image itself. The at-surface reflectivity is calculated with the following equation:

$$\rho_{surf} = \frac{\pi(L_{sensor} - L_p)d^2}{E_0 \cos\theta_z T_z} \tag{1}$$

where Lsensor is at-sensor radiance, Tz is the atmospheric transmissivity between the sun and the surface ($T_z \approx \cos\theta_z$ [10]), θz is the zenithal solar angle, E0 is the spectral solar irradiance on the top of the atmosphere [8], d is the Earth–Sun distance [8], and Lp is the radiance resulted from the interaction of the electromagnetic radiance with the atmospheric components (molecules and aerosols) that can be obtained according to:

$$L_p = L_{\min} - L_{1\%} \tag{2}$$

where Lmin is the radiance that corresponds to a digital count value for which the sum of all the pixels with digital counts lower or equal to this value is equal to the 0.01% of all the pixels from the image considered. Lmin was calculated through DOS (Dark Object Subtraction) technique [11], while the term L1% is given by

$$L_{1\%} = \frac{0.01 \cos\theta_z T_z E_0}{\pi d^2} \qquad (3)$$

B. Multi-spectral indices estimation

Normalized Difference Vegetation Index (NDVI) is a vegetation index used to measure and monitor plant growth, vegetation cover, and biomass production from multispectral satellite data. NDVI is calculated as follows:

NDVI = (NIR - R) / (NIR + R) or (4)

$$NDVI = \frac{B4 - B3}{B4 + B3}$$

where Bi – Landsat satellite band i.

The NDVI is preferred for global vegetation monitoring because it partially compensates for changing illumination conditions, surface slope, and viewing aspect. The principle behind NDVI is that band R is in the red-light region of the electromagnetic spectrum where chlorophyll causes considerable absorption of incoming sunlight, whereas NIR is in the near-infrared region of the spectrum where a plant's spongy mesophyll leaf structure creates considerable reflectance.

This relatively simply algorithm produces output values in the range of -1.0 to 1.0. Increasing positive NDVI values indicate increasing amounts of green vegetation – Fig.2. Thick and healthy vegetation has low red-light reflectance and high near-infrared reflectance, and hence, high NDVI values. NDVI values near zero and decreasing negative values indicate non-vegetated features such as barren surfaces (rock and soil) and water, snow, ice, and clouds. Basically, when the index is below 0, it is the detection of clouds and snow; when it is between 0 and 0.1 it represents rocks, senescent vegetation or soil; when it is between 0.1 and 0.4 it is indicative of cities and when it is above 0.4 it implies the presence of vegetation biomass.

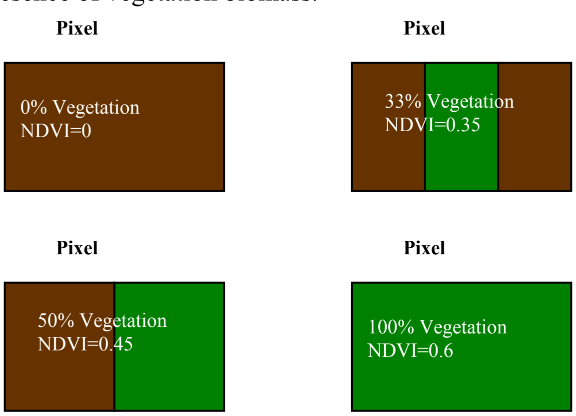

Fig. 2 NDVI Values

The Ratio Vegetation Index (RVI) is the ratio of the highest reflectance; absorption bands of chlorophyll makes it both easy to understand and effective over a wide range of conditions, indicating the amount of vegetation. RVI is defined by the following equation:

$$RVI = \frac{B4}{B3} \qquad (5)$$

The value of this index ranges from 0 to more than 30. The RVI values for bare soils generally are near 1; as the amount of green vegetation increases in a pixel, the RVI increases. The common range for green vegetation is 2 to 8.

The Enhanced Vegetation Index (EVI) was developed to improve the NDVI by optimizing the vegetation signal by using the blue reflectance to correct for soil background signals and reduce atmospheric influences, including aerosol scattering. This VI is therefore most useful in regions where the NDVI may saturate. EVI is defined by the following equation:

$$EVI = 2.5 \frac{B4 - B3}{B4 + 6B3 - 7.5B1 + 1} \qquad (6)$$

The value of this index ranges from -1 to 1. The common range for green vegetation is 0.2 to 0.8.

The Atmospherically Resistant Vegetation Index (ARVI) is an enhancement to the NDVI that is relatively resistant to atmospheric factors, for example, aerosol. ARVI has the capacity to reduce the influence from the atmosphere by employing the blue band (B1 of Landsat TM/ETM+) in conducting atmospheric corrections on the red band. Compared to the red band, the blue band is much more easily scattered by the atmosphere particles, which explains why the sky is usually perceived as being blue.

ARVI is defined by the following equation:

$$ARVI = \frac{B4 - (2B3 - B1)}{B4 + (2B3 - B1)} \qquad (7)$$

The value of this index ranges from -1 to 1. The common range for green vegetation is 0.2 to 0.8.

Increasing drought conditions in Dobrogea region will increase the intensity and frequency of fires in this area - a combination of low precipitation, constant winds, and campfires being the main factors in this kind of disasters.

The index Normalized Burn Ratio (NBR) highlights areas that have burned and measures the severity of a burn from satellite imagery. In essence, the NBR shows the differences in reflected energy between healthy and water-stressed vegetation to determine either the risk of a fire or the level of regrowth that can be expected after a fire occurs.

The formula for the NBR is very similar to that of NDVI except that it uses near-infrared band 4 and the short-wave infrared band 7, since these channels yield the best results for fire risk data:

$$NBR = \frac{B4 - B7}{B4 + B7} \quad (8)$$

Burn extent and severity is judged by computing ΔNBR: the difference between a NBR index calculated from an image just prior to the burn and a second NBR index computed for an image immediately following the burn:

$$\Delta NBR = NBRpre\text{-}burn\text{-}NBRpost\text{-}burn \quad (9)$$

Usually, NBR and ΔNBR maps are generated shortly after a fire burns to get an initial assessment of burn severity. During the next growing season, NBR values are calculated again to assess vegetation survival and delayed mortality.

Estimating the NBR algorithm from an image will yield an output image containing index values constrained to +/- 1. High NBR values indicate burned areas. For ΔNBR, most output values will be between -1 and +1, but scaled by 103, the values will range between -500 to +1300. These values are classified into a "severity" table which is invaluable to those who know how to use the data – Table I.

Table I Burn Severity classification based on NBR index

Severity Level	ΔNBR Range
High Enhanced Regrowth	-500 to -251
Low Enhanced Regrowth	-251 to -101
Unburned	-100 to 99
Low Severity	100 to 269
Low to Moderate Severity	270 to 439
Moderate to High Severity	440 to 659
High Severity	660 to 1300

The Normalized Difference Snow Index (NDSI) is used to identify snow-covered and ice-covered surfaces and to separate snow and ice from cumulus clouds. NDSI is calculated as follows:

$$NDSI = \frac{B2 - B5}{B2 + B5} \quad (10)$$

NDSI values greater than approximately 0.4 are representative of various snow-covered conditions with pure new snow having the highest NDSI values. The NDSI tends to decrease as other features (such as soil and vegetation) are mixed in with the snow.

IV. Problem Solution

Our service meets the requirements of a virtual organization (VO) member who has access to a local database of large satellite images and wants to apply several satellite image processing operations in order to analyze the thermal environment of a region. The operations to be performed are implemented in special client's codes and are to be run on the Computational Grid.

Due to the large size of a satellite image, the full image transfer should be avoided. Therefore, a satellite image will be split into a number of sub-images equal with the number of workstations of the Grid Cluster. The image processing algorithms will also be split into independent tasks that can be performed in parallel and that are requiring similar computing effort.

The design applied is called the Split and Aggregate design which allows parallelizing the process of task execution gaining performance and scalability.

Fig. 3 (http://www.gridgain.com/) shows the logical steps on a Computational Grid: a Grid task splits into Grid jobs that are executed on Grid nodes, the results of the jobs are then aggregated into one, namely the Grid task result.

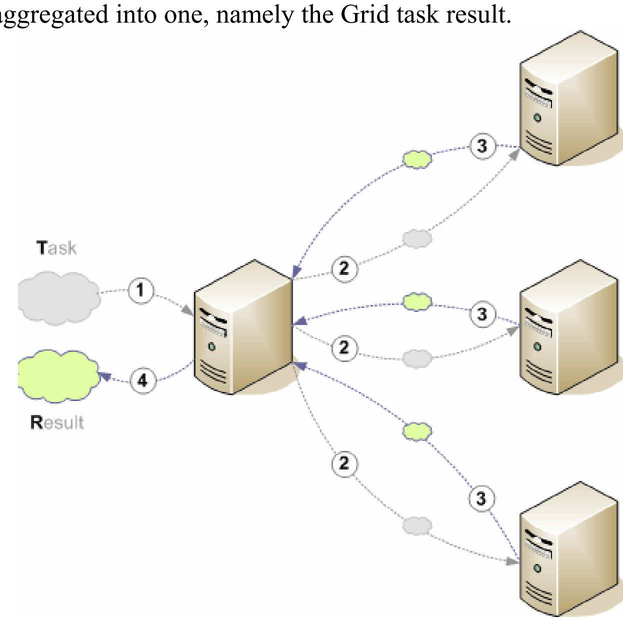

Fig. 3 Split and Aggregate design:
1. Grid task execution request; 2. Grid task splits into Grid jobs; 3. Result of job execution; 4. Aggregation of job results into Grid task result

Due to the large size of a satellite image (up to 1 GB), the full image transfer should be avoided. Therefore, a satellite image will be split into a number of sub-images equal with the number of workstations of the Grid Cluster. The image processing algorithms will also be split into independent tasks that can be performed in parallel and that are requiring similar computing effort.

The following components are needed:

- at the user's node: the satellite bands (Table II), the client's codes and some minimal facilities to access Grid infrastructure,

Table II Files used in the study

Satellite image files	Filename	Type	File Size
ETM+ 2000	Bands: 2,3,4,5,6	tiff	1500x 1500

- at remote computing nodes: the Grid middleware which allows the execution of client's codes.

The client's code consists of three components – Fig.4:

- the Splitter that takes a satellite band and split it into a number of sub-bands;
- the ImageVIEstimator, that receives a pair of sub-bands (eg. pieces of bands 3 and 4 for the computation of NDVI index), applies the estimation algorithm described in Section II-C) and produces the output sub-map;
- the Composer that merges the resulting sub-maps.

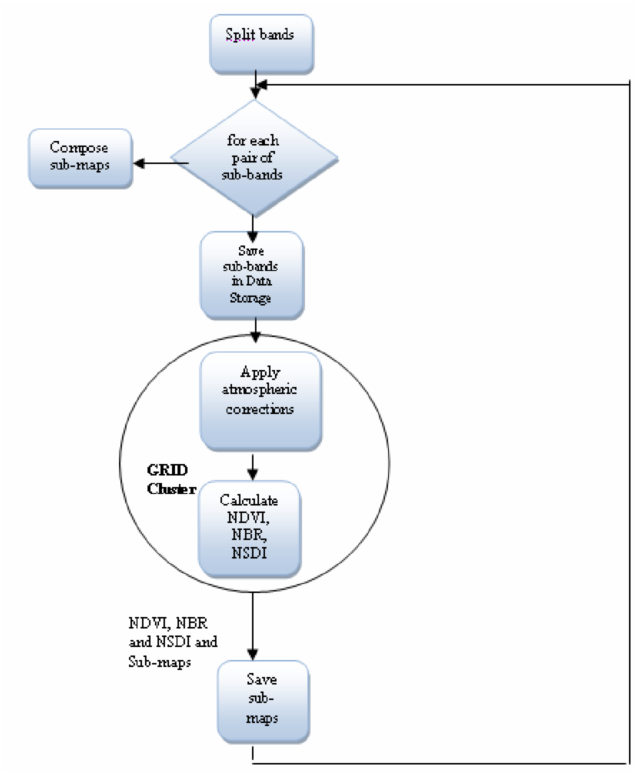

Fig. 4 The logical processing steps for each sub-image

The Splitter and the Composer programs run only at the code's site where the large satellite bands are residing. The ImageVIEstimator and the sub-bands are submitted for processing on the Computational Grid.

The user uploads the image files and submits the jobs to the Grid. After the successful finish of the jobs, the user can download the resulting thematic map.

The service works as follows – Fig.5:

- the user uploads the files using GridFTP and chooses an ImageVIEstimator operation (NDVI, NDSI or NBR estimation);
- the file(s) are transferred to code site;
- the Splitter code is called and the smaller pieces of band(s) are produced as well as the files needed by PBS to launch the ImageProcessor operation on each sub-image;
- The Job Manager of Globus Toolkit 4 take over the files and interpret them and finally PBS sends the jobs on the cluster of workstations;
- After the job executions the output map is stored on the code site;
- The user can access the output map through the user interface.

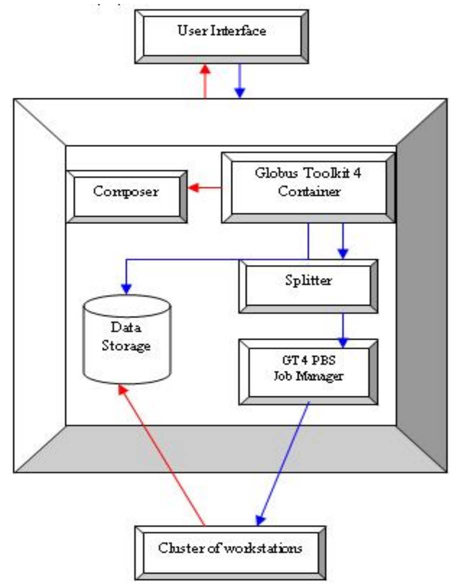

Fig. 5 The components of the service and their interactions

The client's code were written in Java and tested using Python scripts (Fig.6, Fig.7) on the Computational Grid provided by Globus Toolkit 4.

A Web - based client interface (Fig.8), for a service that launches the codes has also been built using JSP, Tomcat/5.5 and MySQL.

The testing environment contains 4 PC nodes (Intel P4, 2.4 GHz, 1GB DDRAM) connected at 100 Mbps and allows processing images of size up to 10 MB. The tests that we performed proved that the presented application is efficient in terms of computation time and easy to use. The application output data consist of the files described in Table III.

```
submitCommandTemplate = "${GLOBUS_LOCATION}/bin/globusrun-ws -submit
        -s -batch -o subimage%02d.epr -F %s -Ft %s -f %s"

# choose randomly the PBS or SGE factory
factoryType =random.choice(['PBS','SGE'])
factory = factoryCatalog[factoryType]

jobDescriptionFilePath = createGridJobDescriptionFile(subimageNumber)

submitCommand = submitCommandTemplate % (subimageNumber,factory,
        factoryType,jobDescriptionFilePath)
print "Preparing to submit job to grid..."
print "Submit command: %s" % submitCommand
try:
      job = popen2.Popen3(submitCommand, capturestderr = True)
      jobOut = []
      jobErr = []
      ret = job.poll()
      while ret == -1:
            jobOut.extend(job.fromchild.readlines())
            jobErr.extend(job.childerr.readlines())
            time.sleep(1)
            ret =  job.poll()
except Exception, e:
            msg = "Error while submitting GRAM WS job: %s" % e
            raise RuntimeError, msg
```

Fig. 6 Python script for code testing

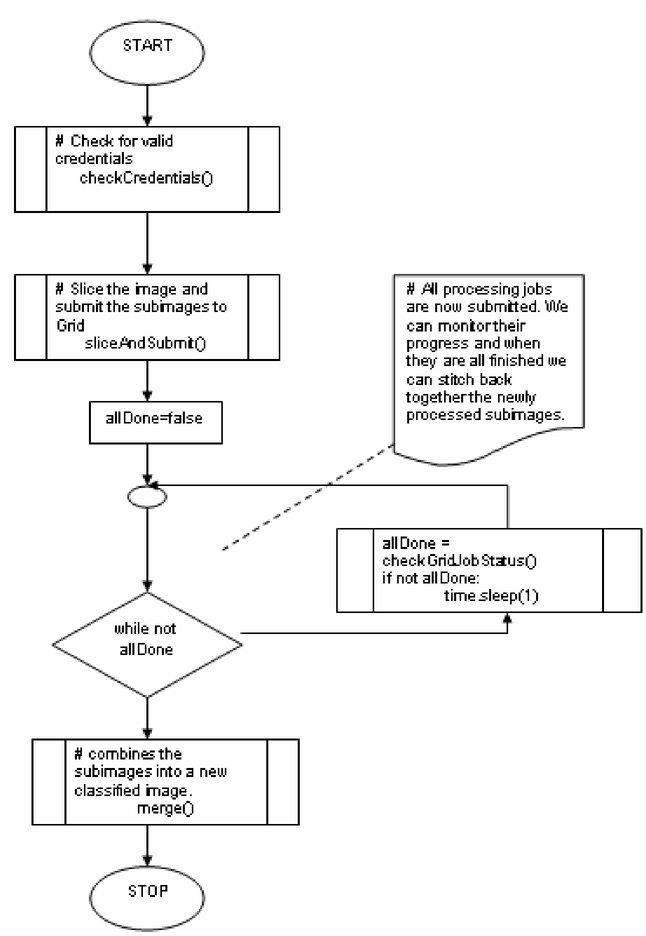

Fig. 7 Python script flowchart

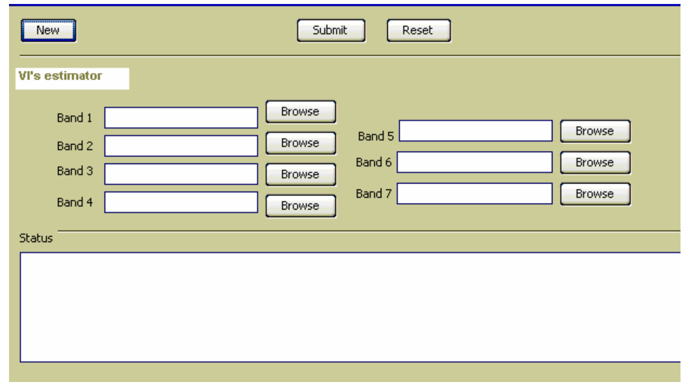

Fig. 8 The user's interface

Table III The output data

File	Description
.txt	Text files with VI's values
.tiff	VI's Map

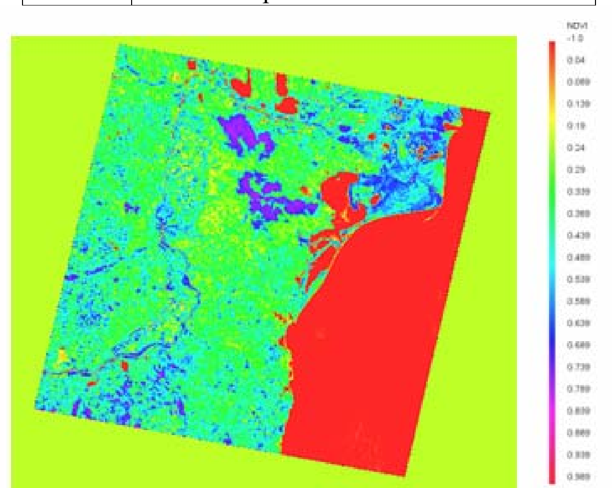

Fig. 9 The NDVI Map

The area used in this study contains diverse land cover types, including vegetative area (dense or sparse), high and medium density built up spaces, and water bodies.

The Vegetation Indices Map (Fig.9) shows that the NDVI values for the study area are consistent with the theoretical values: NDVI of about 0.6 was found for the area with dense vegetation (shades of blue), and NDVI of round 0.4 was reached for sparse vegetation spaces (shades of yellow and green).

V. Conclusion

Remote sensing can assist in improving the estimation of various parameters of great value in water resources management in large cultivated areas and agricultural drought monitoring, Normalized Difference Vegetation Index (NDVI), Ratio Vegetation Index (RVI), Enhanced Vegetation Index (EVI), Atmospherically Resistant Vegetation Index (ARVI), Normalized Difference Snow Index (NDSI) and Normalized Burn Ratio (NBR) are just some of them. The results of this study regarding these parameters are promising and show that the approach can derive reasonable estimates. Grid computing will assist those who want to do such studies but don't have the computational resources they need.

When analyzing remote sensing data and VI's trends and patterns, the various factors affecting VI's values must be considered. Observed changes can be due to complex interaction of all the materials in a scene, how that scene is illuminated and viewed, particular atmospheric conditions at the time of measurement, and sensor functioning.

Because of these limitations, NDVI and other VI's are not perfect measures of vegetative biomass but rather can be thought of as reasonable "surrogates" for vegetation amount, and with careful analysis can be effective for monitoring global vegetation dynamics.

Our future work will focus in developing a Grid system of spatial drought monitoring and assessment over the Dobrogea region. The system will have an Internet server-based architecture to collect and present information from remote sources at one location, and will work in cooperation with regional weather stations.

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Research field include Risk and Vulnerability Management in Construction