## A thesis submitted to the Department of Environmental Sciences and Policy of Central European University in part fulfilment of the Degree of Master of Science

Application of satellite technologies for agricultural monitoring: crop assessment in Russia

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July, 2016

Budapest

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#### **CENTRAL EUROPEAN UNIVERSITY**

### **ABSTRACT OF THESIS** submitted by:

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for the degree of Master of Science and entitled: Application of satellite technologies for agricultural monitoring: crop assessment in Russia

Month and Year of submission: July, 2016.

Nowadays agriculture and food security have become an acute issue. World population is growing exponentially and new ways of cropland monitoring and management should be introduced in order to meet the growing food demand. In this context satellite technologies start playing an important role in agricultural monitoring systems. Coupled with GIS analysis techniques this approach can provide detailed information about crop condition and productivity. The aim of this research is to contribute to food security assessment initiatives by investigating application of satellite technologies in agricultural management and monitoring in Moscow region. Using free and commercial remote sensing images for different time periods, series of maps have been produced identifying problematic areas of cropland requiring attention and intervention of farm management. Through the research several important parameters defining crop health and supporting crop monitoring have been assessed such as overgrown area detection, water and chlorophyll content in vegetation canopy. All steps of the assessment have been assembled in the spatial model allowing automatic satellite data processing and analysis to be made. The model could be used for various crops, and correspondingly, food security assessment at other sites within the study region and worldwide. Not only does the developed algorithm improve agricultural management at the local level and help local farmers, but also it might be interesting for big agrocompanies. The results acquired through this research showed that remote sensing data coupled with statistical information from agrocompanies has high potential to maintain sustainable agriculture and ensure food security.

**Keywords:** Remote sensing, GIS, agricultural monitoring, food security, spatial modelling

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## 1. Introduction

#### 1.2 Background

Nowadays agriculture and food security have become an acute issue throughout the world. Since the population is growing, the importance of food production is increasing as well. In this context, agricultural area management is getting more and more significant for global and local communities. Moreover, cropland management and agricultural productivity improvement play an important role in sustainable development (FAO 2011). It is highly important to maintain food security and according to the FAO report, (2011), agricultural systems should be altered in order to meet food demand in the future. Thus, the methods for cropland monitoring and analysis should be developed in order to improve their management and predict productivity (Sanpedro 2016).

There are many ways to observe and analyze agricultural area and crop conditions. Satellite technology and analysis techniques are now providing detailed information for detecting and monitoring changes in land cover and land use. Remote sensing data is a highly useful tool for the assessment of spatial variability of crop productivity. Band combinations which represent a certain part of electromagnetic spectrum (such as Visible red, green, and blue band and near-infrared (NIR)) can be used for vegetation health analysis. The monitoring of crop cover, vegetation health, crop productivity, and soil moisture can be fulfilled based on this information (Pinter Jr et al. 2003). There have been several studies (Quarmby *et al.* 1993, Kogan *et al.* 2003, Xin *et al.* 2015, Gu and Wylie 2015) to assess vegetation health, estimate the correlation between vegetation indexes and real crop productivity and then to predict the yield based on models for the analyzed region. Some researchers use low resolution images such as data from AVHRR sensor (Quarmby *et al.* 1993, Kogan *et al.* 2003) for NDVI

calculation and global vegetation trend analysis. Others prefer to work with more detailed data such as Landsat data (e.g. Gu and Wylie 2015) which allows monitoring of area patterns larger than 15x15 meters.

#### 1.3 Research aim and objectives

This research aims to contribute to food security assessment initiatives by investigating application of satellite technologies in agricultural management and monitoring. The potential application of satellite technologies is shown on the case study on monitoring cropland condition in the selected agricultural region. In order to achieve this goal, it is necessary to accomplish the following objectives:

- Review existing technologies and data sources which are potentially applicable for agricultural monitoring
- Select case study area
- Select suitable indices and analytical tools for data analysis
- Develop a model for agricultural monitoring

#### 1.4 Thesis outline

The **Chapter 1** provides a background information about food security and agricultural monitoring and aims with objectives are described in it. The **Chapter 2** consists of literature review including overview of agricultural situation and food security in Russia and worldwide. It also covers some theoretical aspects of satellites characteristics providing comprehensive overview of existing sensors and their description. This chapter includes overview of remote sensing techniques and their applications in different domains such as forestry, agriculture, disaster risk assessment and reduction and etc. Another subchapter is dedicated to the geographical information systems (GIS) review with the examples of their applications. In the **Chapter 3** research methodology is described including the process of case study area identification, data collection and data analysis (remotely collected images and statistical information). It also covers the GIS software packages and tool which should

be used for agricultural monitoring. The **Chapter 4** provides the detailed description of all steps of the research. The one of the subchapter includes case study area description and statistical data collection and analysis. Another subchapters describes the process of remote sensing data application for crop condition assessment including overgrown area detection, water and chlorophyll content assessment. The information about image classification for statistical information updating is also presented in this part of the research. The **Chapter 5** is dedicated to discussion of the overall results including series of final maps. All maps are developed by author unless indicated otherwise. The **Chapter 6** provides the summary of the research and conclusions.

## 2. Literature review

## 2.2 Food security and agriculture

Agriculture and food security is an essential part of development and well-being. It influences people's health and life expectancy, agricultural production impacts on biodiversity and the environment as a whole and it affects energy use and the economy as well (FAO 2011). The population growth and increase of reliance on bioenergy apparently can lead to the growth of demand for agricultural products (Foley *et al.* 2011). Nowadays around 800 million people are suffering without sufficient amount of food (Figure 1). In addition, by 2050, the 9 billion global population will need 70% more food than they use today (FAO 2011)



Figure 1 Countries resized according to undernourished population Source: US Department of State 2009

Along with the population growth, climate change and effects of human activity affect agricultural systems and lands. In this context, a possibility of food supply breakdown has become a real problem. It is necessary to monitor and manage properly global and local agricultural activity in order to combat all negative consequences, sustain agriculture production and provide stable access to food products (Justice and Becker-Reshef 2007).

The global concern about food supply and food security appeared in the mid-1970s and during the World Food Summit the food security concept was included to the agenda. Then, in 1983, FAO expanded this concept including stable and secure access to food for people. FAO insisted that the food security concept should "ensure that all people at all times have both physical and economic access to the basic food that they need" (FAO 2003). By the 1990s the food security issue was acknowledged as a significant problem on both the global and individual scale. After the food crisis in the period of 2006-2008, prices for agricultural production increased rapidly and about 80 million of people couldn't afford to buy enough food (Anderson et al. 2013). Nowadays food security is a top priority issue on global and regional levels. There are many organizations and projects (G8 New Alliance on Food Security, New Vision for Agriculture at the World Economic Forum, Food & Nutrition Security Initiatives) which address this topic and seek for a solution of food security improvement, environmental sustainability in agriculture. The key objectives of these initiatives are to provide institutions and public organizations with support, to engage business and society to the process, to help to communicate and share knowledge and results among local, national, regional and global levels. Most of the projects aim to enhance cooperation and partnerships on a global scale and to provide farmers with the equipment and technologies, better seeds to increase yield. Moreover, many initiatives include training and education for farmers in their activity (WFP 2016).

The attaining of cropland sustainability and food security is not possible without proper management of territories and resources and forehanded monitoring of agricultural systems. The World Food Programme in 2016 recognized the urgent

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demand for comprehensive and accurate monitoring of agricultural areas. Since climate change and related fluctuations in frequency of extreme events such as floods and droughts influence negatively and sometimes hardly predictable to agriculture, agrarian systems should be constantly controlled. The functionality of agricultural systems, especially in fragile conditions should be analyzed in detail in order to overcome difficulties. Many programs aim to observe and monitor areas with crops, estimate and predict productivity and indicate possible ways of increasing production from particular area (Justice and Becker-Reshef 2007).

Global projects and initiatives such as Global Agricultural Monitoring (GEOGLAM) developed by The Group on Earth Observations (a partnership of governments and international organizations), Monitoring Agricultural ResourceS (MARS) initiated by The European Commission, Integrated Agricultural Control System (IACS) financed by the European Agricultural Guarantee Fund (EAGF) (IACS 2015, MARS 2015, GEOGLAM 2015) have been launched in connection with a need of agricultural monitoring.

It is well-known that information about any topic plays a crucial role in decision making. Agriculture is not an exception. It is highly important to monitor areas and observe any activity on it to achieve sustainability and make it possible to predict yield. The MARS project which was launched in 1988 aims to provide contemporary technologies and information about crops. In 1993, the participants of this project furthered the elaboration of efficient management of the Common Agricultural Policy providing the technical support and relevant knowledge. After 2000 MARS started working on food security assessment and agricultural monitoring not only in the EU but also outside it. Today, the focus of the project is crop productivity analysis, agricultural activities and the development and support of rural areas. Their approach includes

scientific knowledge that allows early and precise forecasts and estimations to be made. The methods encompass crop production modeling, geo-spatial analysis, agrometeorology, econometrics using a variety of global and national databases. Results and reports are used for the encouragement of agricultural control system development and fostering land parcel management control. The activity within the project also encompasses social-economic factors and considers agricultural problems through rural economies and their impact on the environment. Furthermore, the project aims to assess existing agricultural policies and their influence on different components, seek for approaches to mitigate the climate change consequences through new policies (MARS 2015).

In order to improve the situation with information and raise awareness about agricultural problems, the GEOGLAM project was developed. One of the objectives of this project is to foster communication between countries and international agricultural communities, to help them share relevant and up-to date information about crop conditions and possible crop diseases, to make forecasts of agricultural productivity at local, regional and global levels. The information derived locally about croplands is stored and disseminated through the web application Earth Observations (EO). This program originally is designed for strengthening existing networks in the agriculture of different communities and states and now it allows members to share methods and data, discuss hot topics and find possible ways of solving problems together. The GEOGLAM initiative was approved by the G20 Heads of States' Declaration as a tool for enhancing crop productivity and improve accuracy of its forecasting in all levels (GEOGLAM 2015).

Since the 1960s, the above-mentioned Common Agricultural Policy has been the European Union's most significant common policy. It explains that a huge part of the

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budget is spent on agriculture. However, there are some hindrances in the implementation of agricultural policy and monitoring such as an inappropriate resource and money allocation. In order to solve the problem with payment regulation, the Integrated Administration and Control System (IACS) was created. The main purpose of this initiative is to ensure that money is spent at the right time and in the right way. Through the above-mentioned Common Agricultural Policy farmers are getting funds for subsistence and development. The IACS helps them to gain money when they need it and control the regularity of payments and expenditures. Generally, it is a foundation for the system of agricultural grants from the European Union.

#### 2.3 Overview of agriculture in Russia

Generally, agriculture doesn't play a crucial role in the Russian economy, especially in comparison with the other sectors such as oil and gas industries. The agricultural policy has been modified completely after the collapse of USSR and changes in the economic structure as a whole. There are few stages of the evolution of the agricultural policy in Russia. The first period (1990-1994) was characterized by liberalization of the market. During that period, the State was eliminated from all agricultural activities and initiatives. The government facilitated imports and restrained exports in order to ensure sufficient supply. Then, between 1994 and 1998 the government started supporting agricultural sector through expanding share for agriculture in the budget and regulating agricultural markets (FAP) was organized. There were minimum guaranteed prices for farmers, import hindrances and subsidies for export which attracted people to agrarian system. During the food crisis in 2008, the general agricultural policy shifted towards import substitution again (FAO 2013).

Nowadays, agriculture in Russia accounts for about 4% of value added in the GDP. However, this sector is important in terms of employment. Today approximately 5

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millions of people are occupied in the agrarian system, which is about 10% of total working population. There are two main segments: crop farming and livestock raising. (FAO 2013). According to FAOSTAT (2014), the most cultivated crop in Russia is wheat and in 2009 the total area under wheat was 22% of all croplands (Figure 2).



Figure 2 Arable area in Russia in 2009 (percent of total arable land) Source: FAO 2013

As a result of agricultural reforms, agroholdings have become a common way of cropland management. Generally, an agroholding includes a few agricultural companies which are responsible for crop production, storage and transportation. Within this type of companies it is possible to follow up and check all stages of an agricultural process. Despite of the fact, that it is an efficient approach for agricultural management the share of agroholdings in Russia is still not significant (around 9%). It is mainly explained by obstacles in law and regulations in agrarian sector in general. However, the number of agroholdings have been increasing since 1990 (Uzun *et al.* 2012).

## 2.4 Geospatial technologies for environmental monitoring

## 2.4.1 Satellites overview and applications

Generally, remote sensing is considered as a way of gathering information and data from a distance without any direct contact with objects using tools for measuring electromagnetic radiation reflected from the Earth's surface (Figure 3)( (Schott 2007).



Figure 3 Basic principle of remote sensing data collection Source: Baumann 2010

Sensors on satellites receive information about the Earth's surface in different parts of the electromagnetic spectrum (Figure 4). Different objects on the Earth emit various amount of energy, thus the image of the surface based on energy variation can be created. Whereas human eyes can see variation in the visible area of the electromagnetic spectrum, sensors can detect information in non-visible portions of the spectrum. Consequently, it allows to identify changes in chemical elements content in plants, differentiate variety types of objects and obtain information about their characteristics (Baumann 2010).



Figure 4 Electromagnetic spectrum Source: Baumann 2010

The most common satellite characteristics of satellite images are based on three components: spectral, spatial and temporal resolutions. The spectral resolution describes the amount of spectral bands (spectral channels) used for collecting information about the Earth's surface on a particular sensor (Liu and Mason 2016). Often satellites record different areas of the spectrum at the same time creating multi-images. These bands (scanned regions) are identified in nanometers (nm). Combining different bands it is possible to obtain various color composite images (Turner *et al.* 2007). There are many ways to compose bands and each particular combination suits better for detecting different surface characteristics. Some combinations allow the water content to be identified better or different crops can be picked out, others can be used for urban studying and level of contamination estimation (Table 1).

## Table 1 Different bands and their usage

Image composite	Description
	Red-Green-Blue This combination is often called "natural color". In this combination ground objects look similar to their appearance to human eyes. It is mostly used for urban and aquatic habitats studies.
	Near infrared (NIR)-Red-Green This combination is often called "false color". It is used for looking at vegetation, crops and wetlands. In this combination the most healthy and dense vegetation is getting more vibrant and red.
	Near infrared (NIR)-Mid infrared 1 (SWIR 1)-Red This combination is useful for differentiation land from water. Also different vegetation types are identified more precisely. It is easier to pick out inland water bodies and streams using this combination. Two infrared bands allow water content in soil and plants to be distinguished.
	Mid infrared 2 (SWIR 2)- Mid infrared 1 (SWIR 1)-Red This combination is closed to the previous one, however it provides better atmospheric penetration allowing differentiate different types of vegetation and reveal subtle differences in surface conditions.
	Mid infrared 1 (SWIR 1)- Near infrared (NIR)-Blue This combination is mostly used for the agricultural monitoring and different crops detection (they are displayed as a vibrant green). This bland of bands helps to pick out bare earth that appears as a magenta color.

Mid infrared 1 (SWIR1)-Green-Blue This combination is useful for differentiation differences in bare earth with sparse vegetation.
Near infrared (NIR)-Mid infrared1 (SWIR1)- Coastal blue The coastal blue band in this combination provides an information about fine particles (dust and smoke, for example).
Near infrared (NIR)-Red Edge-Red The Red edge band in this combination allows to depict chlorophyll content in plants and even subtle differences in the vegetation canopy picked up well.
Mid infrared 2 (SWIR 2)- Mid infrared 1 (SWIR 1) – RedEdge This combination suits better for showing up of plants and built-up features.
Green-Blue-Coastal blue This combination is useful for bathymetric analysis. This combination is free from additional surface reflection which provides better quality and water penetration.

Information in sensors is stored as a grid and the smallest area unit is digital image is a pixel. The spatial resolution of an image is determined by size of a pixel. The finer the grid and the smaller one pixel, the better visualization of object's details (Figure 5).



Figure 5 Concept of spatial resolution Source: Satellite Imaging Corporation

Spatial resolution value is usually represented in meters or centimeters. For example, if an image has resolution of 10 meters it means that objects wider or longer than 10 meters might be distinguished at the image as separable objects (Figure 6). Nowadays, the best spatial resolution from satellites is 0.41 m. The images with up to 4 m. of spatial resolution are recognized as high spatial resolution images, images with 30 – 1000 m. are considered as low spatial resolution production (Liu and Mason 2016).



Figure 6 Satellite images with different spatial resolution Source: NASA Science 2016

The temporal resolution represents the time interval of revisiting frequency of a particular sensor for the same area. It depends on altitude, orbit and viewing angle of the satellite. The temporal resolution varies from 2-3 days to years (Satellite Imaging Corporation 2015).

Nowadays there are variety of remote sensing data which is characterized by different spatial resolution and coverage, sensitivity and accuracy, number of sensors and frequency of observation. Contemporary technology plays a significant role in a comprehensive understanding of processes on the surface and their consequences. There are free data that is possible to download through Internet without any fee and commercial data (Marghany 2014). Generally, commercial data sets are characterized by better spatial resolution and a possibility of ordering new data for a particular area of interest (Table 2).

Data	Description
AVHRR	6 spectral bands (spatial resolutions – 1 km)
MODIS	36 spectral bands (three spatial resolutions - 250m, 500m, and 1,000m)
Santinel-2	12 spectral bands (spatial resolution -from 20. m to 10 m.)
Landsat	8 spectral bands data (spatial resolution - from 30. m to 15 m.)
SPOT	5 spectral bands data (spatial resolution - from 1.5 m to 20 m.)
RapidEye	5 spectral bands (spatial resolution -5 m.)
WorldView-2	8 spectral bands (spatial resolution – 0.5 m.)
Radarsat – 2	18 modes (spatial resolution - from 1 m to 100 m.)
TerraSAR-x	7 modes (spatial resolution - from 0.25 m to 40 m.)

Table 2 Variety of remote sensing data

GIS and remote sensing techniques monitor the spatio-temporal and dynamic changes in land use/land cover at regular intervals using multi-temporal remote sensing satellite data (Turner *et al.* 2007). These data and tools play a significant role for natural resource analysis and management. Satellite images can provide spatial resolutions of less 0.5 m. for analysis on local level and up to 1000 m. for global monitoring. Remote sensing techniques can be incredibly useful for tracking vegetation and ecosystem dynamics on global and regional level, for dangerous accidents monitoring, for analysis of geological components, hydrology and meteorology, land cover and land use changes detection (Satellite Imaging Corporation 2015).

Data from the AVHRR sensor (Advanced Very High Resolution Radiometer) is primarily used for the global monitoring of land and ocean temperature changes and defining vegetation trends. Using red and infrared channels of that sensor it is possible to determine water-land delineation and to model vegetation stratification. With bands' range between 3.55 - 3.93 micrometers and 10.5 -12.5 micrometers information about day and night water surface temperate and snow cover extent can be derived (NOAASIS 2015).

Information derived from the MODIS observations (The Moderate Resolution Imaging Spectroradiometer) can be used for the long-term local and global analysis of the Earth's surface, water and atmospheric properties (Shao et al. 2011). The MODIS data is characterized by a wide range of applications such as assessment of global climate models (Oleson *et al.* 2003), land cover type identification and mapping (Zhang X. *et al.* 2008), forest cover analysis and vegetation changes (Hansen *et al.* 2008), agricultural monitoring and crop conditions' observation (Sakamoto *et al.* 2009;Zhang M. *et al.* 2014) and crop productivity analysis, yield assessment and prediction (Chen *et al.* 2006;Leroux *et al.* 2016;Sakamoto *et al.* 2009).

Another widely used free datasets from Earth observation satellites are Landsat images. Datasets are useful for land cover determination, vegetation health observation and geologic characteristics. This mission represents the longest continuous global data collection of the surface. The program was launched in 1975 and it has been consistently collecting information for over 40 years allowing historical archive of images for the entire globe to be created (Landsat Science 2016). The resolution of 15 m. and 30 m. provides an ability to analyze objects on local level. Along with the longest continuous records of the Earth surface which gives the possibility to assess changes through time, made Landsat data unique and valuable for scientists (Hansen and Loveland 2012). There are a wide range of Landsat images applications such as a mapping geological features, water objects and land-water boundaries, a determination of vegetation type, land use type classification, flooding, agricultural and urban growth monitoring. For example, for land managers and decision makers it is highly important to understand conditions of vegetation on their land parcels and have

a possibility to control it remotely. In this case, Landsat data plays a crucial role in the land management. Images can be used for irrigation and fertilization planning, monitoring of crops' growth and identification of problems in a crop growth process (Landsat Science 2016).

Some authors (Hansen and Loveland 2012, Gómez *et al.* 2016) also mention data from Sentinel mission as an additional source of free data for different type of analysis of object on the Earth. Sentinel-2 was launched in 2015 and it provides high-resolution optical imageries for the entire globe every 5-10 days. The main goals of that program is to provide continuous and consistent global acquisitions of high-resolution images and information for generation of land cover and land use maps, to gather some geophysical variables. Sentinel-2 project aims to contribute to the global largest single earth observation Copernicus program and improve information comprehensiveness for climate change observation, land monitoring, and emergency management (Drusch *et al.* 2012).

Along with free data, images from commercial satellites can be used for environmental processes observation. Data with better resolution is highly useful for local analysis and it can be used for verification and amendment of results. Some commercial datasets such as WorldView-2 collect information in 8 bands and produce high-resolution multispectral images. It provides data in coastal band which is suited for bathymetric studies, for water quality analyses and assessment of chlorophyll absorption. The new generation of satellite also gives an ability to use yellow and red edge channels for better and more precise classification and vegetation type identification (Cristina *et al.* 2012).

In this research data from RapidEye satellite is used. The RapidEye Multispectral Imager provides with the data in five spectral bands (blue, green, red, red edge and

near-infrared). The resolution of 5 m. of these images are lower than WorldView-2 resolution (0.5 m.) and as a consequence, the RapidEye data is less expensive and more commonly used for academic research purposes (Onur and Süha 2012; Marghany 2014). The images from RapidEye satellite are used widely to monitor natural disasters, land use and land cover map creation and vegetation health analysis. Using combination of these bands chlorophyll map can be developed. These map of a cropland represents the spatial variation of relative chlorophyll content. In conjunction with vegetation indices it allows to monitor a crop and soil conditions and better predict a future crop yield (Kross *et al.* 2015). Moreover, the red edge band allows to estimate spatial variability of crop characteristics such as green ground cover. This variable is highly important for agricultural management and is often used for crop yield analysis (Zillmann *et al.* 2015).

#### 2.4.2 Remote sensing techniques and applications

There is a wide range of applications of remotely collected data in different domains such as forestry, agriculture, disaster management and etc. Not only do satellite techniques provide information about visual condition and changes on the Earth surface, but also these data can be used for further analysis in order to obtain detailed information.

Despite the fact that photosynthesis can not be measured directly by satellites, remote sensing techniques can provide information for photosynthesis estimation through different vegetation indices calculation. Basically, vegetation indices are different mathematical combinations of spectral bands. The first index was developed after first Landsat mission launch in 1970s (Tucker 1980). Nowadays, there are hundreds of different indices that can be used for a wide range of assessments such as biomass calculation, vegetation health monitoring and plants' vigour analysis.

There are many vegetation indices which can characterize the vegetation conditions and photosynthetical activity at a certain time. Vegetation indices have been widely shown to provide valuable measurements of vegetation activity and conditions (Bounoua *et al.* 2000, Tucker 1980).

One of the most common used index is The Normalized Difference Vegetation Index (NDVI) which can be used to crop yields' estimation, plants' health analysis or pasture performance (Bounoua et al. 2000). Usually NDVI index takes the value from +1.0 to -1.0. Bare surface or sand typically are characterized by low values (0.1 or less). Scarce vegetation such as shrubs and bushes shows values from about 0.2 to 0.5. Dense and healthy vegetation often result in high values (more than 0.6-0.7) (Tucker 1980). The calculation is based on the ability of health vegetation to absorb most part of visible spectrum and reflect a large amount of the near-infrared lights. Whereas the reflection of unhealthy or sparse vegetation is mostly consist of visible lights, the reflection of healthy vegetation affected mostly by wavelength in near infrared part of the spectrum. Mathematically this index is a ratio of spectral reflectance values of red band (Red) and near infrared (NIR) (Figure 7) (Tucker et al. 1994):



Figure 7 Vegetation reflectance in different spectral bands Source: NASA Science 2016

NDVI is widely useful for crop identification (Li *et al.* 2015), biomass estimation (Kross *et al.* 2015) and crop productivity assessment and yield prediction (Quarmby *et al.* 1993, Kogan *et al.* 2003).

Another index which is also suitable for that kind of vegetation analysis is Leaf Area Index (LAI). LAI is based on the calculation of green leaf area per unit ground surface area (Marghany 2014). In remote sensing techniques LAI is often to calculation of Enhanced Vegetation Index (EVI). EVI index is similar to NDVI, however due to blue bands in the calculation it allows to avoid distortions by aerosols and other atmospheric particles:

EVI = 2.5 \* ((NIR-Red)/(NIR + 6\*Red – 7.5\*Blue +1).

Thus, this index is useful for plant growth process observation (Zhao *et al.* 2007), land cover classification (Zhang X. *et al.* 2008), for biomass assessment (Kross *et al.* 2015) and also for vegetation health analysis.

Another important component, water content in a plant and soil can be calculated through variety of indices such as Water Deficit Index (WDI) and Normalized Difference Water Index (NDWI). It was proven that these indices are known to be correlated to the water content in plants (Gao 1996).

Vegetation can be affected harshly by water stress during dry period of time. It influences on plants growing process, can impact a future harvest and potential yield might be reduced. In order to prevent negative consequences, it is important to observe water content in vegetation canopy and recognize water stress. Remote sensing techniques allow to identify problematic crop parcels and inform farmers and stakeholders at early stages of plant water stress improving agricultural management and minimizing risk. The mentioned above indices are known to be correlated to the water content in plants

WDI represents the ratio of actual and potential evapotranspiration and this index is often used for creation of water conservation maps, irrigation assessment and identification of lands with the greatest evaporative water losses (Moran et al. 1994). This index suits perfectly for water bodies' detection and assessment of flooding impact. Along with WDI index, NDWI can be used for water content assessment. The NDWI calculation includes Short Wave Infrared (SWIR or MidIR) band which allows water content assessment to be made more precisely. The spectral reflectance in that portion of spectrum is highly controlled by amount of water in a leaf structure. The reflectance in the SWIR (MidIR) interval is affected by leaf water content and leaf internal structure, whereas the reflectance of Near Infrared band detects dry matter content and it is not affected by vegetation water content. Thus, the combination of both bands allows minimizing variations of leaf mesophyll structure and dry content and amend accuracy of water content assessment. The usage of SWIR (MidIR) channel in the calculation allows to eliminate cellulose absorption effects. Therefore, this index can be used for more precise liquid estimation and better differentiation of dry vegetation and soil (Gao 1996).

Nowadays, techniques for environmental observation have been developing and the presence of Red Edge channel broadens possibilities of remote sensing analysis. There are many studies where that part of the spectrum is used for obtaining more detailed information about vegetation (Kross *et al.* 2015;Shang *et al.* 2015). The red edge part is located between the red band and the NIR band in the spectrum (Figure 8). This band is located in that part of the spectrum where reflectance sharply changes from Red to NIR portion.



Figure 8 Red Edge band location in spectrum Source: Eumetrain 2010

Using Red Edge band it is possible to improve the accuracy of an assessment of vegetation health. The Red Edge Normalized Difference Vegetation Index which is similar to NDVI, but Red Edge band is used in the calculation instead of Red. The Red Edge channel from RapidEye and indices calculated based on this band are commonly used for detection plants in stress, biomass assessment and for crop type identification (Kross *et al.* 2015, Yeom and Kim 2015). As it was said above, using NIR band it is possible to analyze leaf structure whereas in the Red part of the spectrum the chlorophyll absorbs light. Thus, the Red Edge region shows a high potential for chlorophyll content assessment (Zillmann *et al.* 2015).

Thus, using combination of other bands and red edge channel chlorophyll (Chl) map can be developed (Figure 9). Information about chlorophyll content plays an important role in remote sensing applications for agricultural monitoring since it shows strong correlation with leaf nitrogen content. The nitrogen content in plants is highly important indicator in many fields such as agriculture, forestry and water monitoring. Assessment of nitrogen content in plants is significant part of different agricultural practice planning such as application of fertilizers or establishing of irrigation regime. Lack of nitrogen content allows to detect problematic areas within a crop parcel

minimizing risks of crop failures. Despite that remotely collected data can not provide direct information about amount of nitrogen in leaves, through monitoring of chlorophyll content it is possible to observe and estimate leaf nitrogen content (Zillmann *et al.* 2015). Furthermore, chlorophyll content can be used for water quality analysis and water transparency (Secchi depth) assessment (BlackBridge 2012).



Figure 9 Chlorophyll map based on RapidEye data Source: BlackBridge 2012

There are many indices suited for chlorophyll content assessment. Among the wide range of chlorophyll-related vegetation indices, the Improved Modified Chlorophyll Absorption Ratio Index (MCARI) which allows to chlorophyll content to be estimated with a higher accuracy. The results has proven that this index has higher linearity with chlorophyll content and the usage of that index can minimize the sensitivity to the reflectance contribution from the surface (Wang *et al.* 2011).

Land cover classification and crop type identification is also one of the possible application of indices with red edge band (Zillmann et al. 2015). Some studies (Shelling 2010) suggested that accuracy of classification is getting higher with the analysis of red edge band and vegetation indices such as Normalized Difference Red Edge Index (NDRE) or MCARI. It allows better differentiate different types of land cover and providing information about dry matter structure long with wet content in vegetation canopy.

#### 2.4.3 Geographic information systems (GIS) and data processing

There are many ways and approaches of remote sensing data analyzing and processing. Previously, in the late 1960s, raster data and vector data were processed and analyzed separately. However, today the GIS software allows both images and vector data to be assembled in one working environment. The procedure of remotely collected processing in GIS usually include several steps such geometric correction, histogram adjustment (non-linear stretching is often applied for data with multi-modal distribution), color composition (for creation of RGB image, for example) and multi-band manipulation (Liu and Mason 2016).

Data taken at a big distance from the Earth characterized by different distortions because of an atmospheric fraction. A sensor itself affects the way of measuring of radiant energy. Moreover, time when data is being collected influences an electromagnetic energy capturing. Thus, a quality of the image might be degraded and needed to be improved (DeFries 2013). After radiometric and geometric restoration images can be analyzed through color composite generation. It implicates the process of combining different bands according the research purposes. Filtering is also one way of processing remotely sensed images. It includes edge enhancement (crispening) or image blur disposal.

There are many ways of interpreting satellite information. Variety of methods such as unsupervised classification, supervised image classification and object-based analysis are commonly used for an image interpretation (Liu and Mason 2016). Any classification process implicates pixel sorting to an exact amount of individual classes according to pixel values. Unsupervised classification doesn't require any knowledge about study area and pixel values. Usually this method of image classification is based on clustering algorithm. That algorithm allows to assemble pixels with the same values

into the groups. In this case, user is not involved in a process of the pixel differentiation. However, a user can specify some basic information about clustering options such as type of clustering (usually it comprises K means, ISODATA and Narenda-Goldberg clustering), spectral channels which should be used in the classification and the final number of categories. Also it is possible to change some processing parameters such as maximum iterations, skip factors for X and Y axis and set a convergence threshold (Figure 10).

Unsupervised Classification		
Input Raster File: (*.img) 3764607_2015-06-07 🗸 🖨	Input Signature File: (*.sig)	
✓ Output Cluster Layer Filename: (*.img)	Dutput Signature Set Filename: (*.sig)	
Clustering	g Options:	
Method: <ul> <li>Initialize from Statistics</li> <li>Use Signatures Means</li> <li>K Means</li> <li># of Classes: 10</li> <li>Isodata</li> </ul>		
Initializing Options	Color Scheme Options	
Processing Options:		
Maximum Iterations: 10	Skip Factors:	
Convergence Threshold: 0.9	50 ÷ × 1 •	
Classify zeros Add 1:1 Iteration		
OK Batch AOI	Cancel Help 🗶	

Figure 10 Basic parameters for unsupervised classification

This approach is mainly used when you don't know exactly the characteristics of the area and there is no previous field data for the area of interest. There are many advantages of using that technique of classification such as easily obtained thematic image without any field work. However, one of the disadvantages of unsupervised
classification is that the results can produce too many classes and the further analysis such as cluster combination is needed in order to obtain a realistic map (Marghany 2014). Often that type of classification is used as an intermediate step for supervised classification.

Supervised classification as advanced method of satellite images interpretation. It allows to obtain quantitative information from the images based on the knowledge of the area. Remote sensing data analyst specifies the particular land cover class based on detailed information about an area of interest. This process is so called "training" of the software. During that process a user determine polygons on the image that are known to be representative of a certain land cover class. After that training, software is able to compute spectral characteristics within each training area and define the mean and variance of the types for further classification. During that process each pixel is assigned to a particular category which it most closely coincides and a signature file is created. Afterwards it is possible to use some parametric rules or algorithms such as Maximum Likelihood, Maximum Distance, Minimum Distance, Spectral Angle Mapper, Spectral Correlation Mapper or Gaussian (Figure 11).

5 Supervi	sed Classification
Input Raster File: (*.img) 3764607_2015-06-07_re 🗸	Input Signature File: (*.sig)
Classified File: (*.img)	Distance File
Attribute Options	
Fuzzy Classification	2 A Best Classes Per Pixel
D	ecision Rules:
Non-parametric Rule:	None
Overlap Rule:	Parametric Rule 🗸 🗸
Unclassified Rule:	Parametric Rule 🗸 🗸
Parametric Rule:	Maximum Likelihood 🗸
Classify zeros	Maximum Likelihood Mahalanobis Distance Minimum Distance Spectral Angle Mapper
OK Batch	Spectral Correlation Mapper

Figure 11 Basic parameters for supervised classification

Maximum likelihood method is the most commonly used for supervised classification. It implies that each spectral segment can be described by a multivariate normal distribution. However, in order to obtain an accurate result a mean vector and the covariance matrix should be chosen correctly. Therefore, supervised classification is more controlled by a user and it requires more profound knowledge about a studying area. Since this type of classification involves more steps of analysis and requires field work or signature file with "samples", supervised classification is more accurate approach for satellite images interpretation (Marghany 2014).

The above-mentioned methods are so called pixel based approaches of image classification which have been prevailing concepts since 1980s. Today, the new

paradigm of object-based or object oriented image analysis is getting more commonly used. It includes "older segmentation, edge-detection, feature extraction and classification concepts" and this type of classification is highly scale-dependent. Whereas pixel-based methods produce classified pixels, the result of object-oriented classification is objects with different shape and scale. This process of multi-resolution segmentation encompasses analysis of texture, geometry, context and pattern (Figure 12). Thus, a homogenous image depicting particular objects can be produced (Blaschke *et al.* 2014).



Figure 12 Example of object-oriented classification Source: LAND INFO Worldwide Mapping 2016

Any manipulation with remotely sensed images or other type of spatial data are fulfilled in GIS packages. Nowadays, GIS tools allow users to collect, store, modify and display spatial data in different ways. GIS software provides a possibility to use any kind of remote sensing data and interpret it. The companies like ESRI (ArcGIS) or Hexagon (ERDAS IMAGINE) provide software packages for remotely sensed data manipulation, transformation and interpretation. With spatial modeling tool it is possible to create a model which suits your research purposes. Spatial modelling is a way of working with data and combining functions for raster or vector analysis. It uses visual programming language for creating workflows of data analysis and management, but it is displayed in a user-friendly environment. A spatial model chains together sequences of processes and geoprocessing tools which can be used for different type of analysis such as slope calculation, change detection, flood area calculation and potentially suitable area detection (Figure 13) (Maguire *et al.* 2005).



Figure 13 Example of spatial model for slope and aspect extraction in ERDAS IMAGINE

## 3. Research Methodology

### 3.2 Selection of case study area

Today there are many private agroholdings in Russia. However, there is no official statistic information since the concept of such type of organizations are not described in the Russian regulations. Russian legislation does not contain requirements for the provision of consolidated financial reports from the all enterprises belonged to the same agroholding structure. Government authorities in municipalities and constituent units also are not able to provide complete information about agricultural holdings, since often their subsidiaries are located in several municipalities and regions of the Russian Federation (Uzun *et al.* 2012). Thus, the information about crop types, plant conditions and the observation of growth process is highly important for local farmers and agrocompanies.

For this research the correspondence with several agroholdings in Russia which have croplands in Moscow region and surrounding areas have been carried out. The main objective was to investigate the statistical information and its content of companies. In order to reach the goal of the research, statistical data about a yield and a crop type for a few period of time should be gathered. After a few negotiations and meeting with the experts from agrocompanies it turned out that agrocompany Agroosnova has appropriate information and it is willing to share their data.

### 3.3 Data collection

### 3.3.1 Remotely sensed data

For the research accomplishment different spatial data is required. Following data can be used for the research purposes (Table 3):

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Data	Source
AVHRR	http://noaasis.noaa.gov/NOAASIS/ml/avhrr.html
MODIS	https://lpdaac.usgs.gov/products/modis_products_table
Santinel-2	https://scihub.copernicus.eu/dhus/#/home
Landsat	http://glovis.usgs.gov/
SPOT	https://www.geo-airbusds.com/en/143-spot-satellite-imagery
RapidEye	http://www.satimagingcorp.com/satellite-sensors/other- satellite-sensors/rapideye/
WorldView-2	https://www.digitalglobe.com/
Radarsat – 2	http://www.asc-csa.gc.ca/eng/satellites/radarsat/radarsat- tableau.asp
TerraSAR-x	http://terrasar-x-archive.infoterra.de/

Table 3 Potential data sources

### 3.3.2 Statistical data

Statistical data in agrocompanies are stored in many ways such as spatial databases or even as some paper sketch from the field. If it is digital statistical data, it can be in CSV. or other excel formats which usually includes following information: name of the area, name of the cropland, total area, category, purpose, type of usage, legal status, cadastral number, type of crop, name of organization, occupation of the organization, and responsible person (Figure 14).



Figure 14 Example of statistical data as table

Sometimes agrocompanies with more advance infrastructure possess some spatial data and information about crops, harvest and etc. can store in spatial databases or shapefiles as attributes (Figure 15).

iene	al Attribute	в			
	Name	Value			
	FIELD	ЛУ161			
	SECTION	0			
	SEM_703	345			
	SEM_704	22			
	YEAR	2016			
	PLAN				
	FACT		N		
	CULTURE	Озимая пшеница	Pb		
	GR_TYPE		Ni		
	RAVINE		Ha		
	GR_ST		Δs		
	INTENSIFIC	Normal	Mn1		
	SEM_713		Cr		
0	AREA_DOC	55,6	Vegetation	wheat	
			ObjectCode	0	
			ObjectKey		
			ObjectID	230	
			ObjectName	полигон	
			ID1	221	

Figure 15 Example of statistical data as attribute information

## 3.4 Data analysis

### 3.4.1 Geospatial data processing

There are variety of GIS software for spatial data analysis from different companies. During this research ERDAS IMAGINE and GeoMedia Pro software are used for the main stages for analysis. Also the software SNAP for Sentinel-2 data transformation and visualization is used in order to create the proper image for further analysis in GIS software. For further analysis of the raw satellite data, multicolor composite images should be created. Generally, data from satellites (Sentinel-2 or Landsat data, for instance) is provided as a set of separate images which represent certain channel. To obtain the composite images the Layer Stack option in ERDAS IMAGINE software can be used (Figure 16).



Figure 16 Function for band combination in ERDAS IMAGINE

For the current research we need several band combination such as combination of 6-5-2 or 5-4-3 bands of Landsat 8 which suits for agricultural monitoring purposes and natural color combination (4-3-2) for general observation of crop parcels.

Using different spectral bands it is possible to calculate vegetation indices such as Normalized Difference Vegetation Index (NDVI), Improved Modified Chlorophyll Absorption Ratio Index (MCARI) and NDWI which are required for this research (Table 4). NDVI can be calculated using Landsat data or Sentinel-2 images. MCARI index should be calculated using RapidEye data since this satellite is equipped with the sensor for red edge information capturing. For the NDWI estimation the Sentinel-2 data should be used because for the calculation of that index the MidIR or SWIR band is required (MidIR ~1241 nm). The obtained datasets can be used for classification or creation of categorized images later on. The SWIR reflectance allows to track changes the water content and the mesophyll structure in vegetation canopies, while NIR depends on inner leaf structure and dry matter content. Thus this index which includes both bands allows to obtain the vegetation water content with higher accuracy (Tucker 1980).

CEU eTD Collection

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		_
Index	Expression	Data
Normalized Difference Vegetation	(NIR – Red)/(NIR + Red)	Landsat-8
Index (NDVI)		
Red Edge Normalized Difference	(NIR – RedEdge)/(NIR + RedEdge)	RapidEye
Vegetation Index		
Improved Modified Chlorophyll	(1.5*(2.5(NIR – RedEdge) – 1.3(NIR –	Sentinel-2
Absorption Ratio Index (MCARI)	Green)))/SQRT((2*NIR + 1)^2 -	
	(6*NIR - 5*SQRT(RedEdge)) - 0.5	
The Normalized Difference Water	(NIR - MidIR) / (NIR - MidIR)	RapidEye
Index (NDWI)		_

Table 4 Expressions for vegetation index calcultaion

Combining different images with vegetation indices such NDVI and NDWI, the map of crop parcels requiring farmers' and stakeholders' attention can be derived.

For the crop identification the classification of images should be fulfilled. In our case, unsupervised classification should be used with further verification of results in the field. Afterwards it is possible to create signature file using information about crop type from the field work. The fact that the real information from the field is used should improve the accuracy of classification and identify other parcels with a certain crop type more precisely. Moreover, the combined information about crop type can be used for identifying some mistakes in statistical data and for its updating.

## 3.4.2 Combination of statistical and image data

For the comparison of statistical data from agrocompanies and information derived from satellites, it is necessary to convert raw text with statistic into any spatial files. Different geocoding tools can be used for that purposes. In this research the statistical information should be converted and adapted for the further analysis in GIS software packages. Later the resulting file in excel format should be joint to the vector data with the crop parcels (Figure 17).

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Left side of join:	Right side of join:	Output join as query     Query name:	
F3         ^           F4         F6           F7         F9           Реестр земельных участков 000(√	ID1	Description:	
Selected attribute pairs:		tributes	ile:
Type of join ─Type of join 「Inner C Right outer C Left o	uter C Full <u>o</u> uter	Display join in data <u>w</u> indow Data window name: DataWindow1	Ŧ
		OK	Cancel

Figure 17 Tool for data combination from different sources

### 3.4.3 Spatial model development

Using spatial modeling functionality several algorithms should be developed for data analysis. The calculation of indices and identification of problematic area should be included in one chain using analytical operators from the existing list in ERDAS IMAGINE software (Figure 18)



Figure 18 Operators for spatial model development

Afterwards the convenient tools for end users can be created for the executing of the developed models. Users can simply add data in your model without any additional changes of the parameters and receive the results. In the image (Figure 19) the examples of final spatial models for users are shown. It is another convenient way of spatial model representation.

oprocessing	-	Geoprocessing
Processes List Selected	My Processes	Processes List Selected My Process
Input Data Input NLCD Land Cover:	▲	Painted_Relief Painted Relief: Any map based off of elevation data that appears to be, or is, three-dimensional. May also be referred to as a shaded relief map
Input DEM Elevation File (DTEI similar):	D2 or	Input Data
Input DEM Elevation Units:		
Native Type	* •	
	Execute	Execut

Figure 19 Layout of spatial models for end users

# 4. Monitoring agricultural activities

## 4.2 Case study area description

The case study area has been selected after several consultation with the agrocompanies, the experts from the field and the assessment of satellite images existence for the research purposes. The area of interest is located in the Moscow region with the total area of 51 sq.km (Figure 20). Depending on the year, the parcels are covered with wheat, barley and corn. Generally, the Moscow region is situated in the basin of the Volga, Oka and Moscow rivers and its total area is about 46 000 sq. km. The climate of the region is continental, however it is not characterized by severe winters or extremely hot summers. Also deviations from standard conditions are quite often in that region. During winters it could be some long thaws and conversely long-run rains and sudden cold spells may occur in summer. The total amount of days with an average temperatures above zero is approximately 200 days with sunny period of 1500 hours per year (Moscow City Environmental Profile 2000).



Figure 20 Case study area in Moscow region

## 4.3 Statistical data collection and analysis

The statistical information from Agroosonova organization consisted of several string files which were converted and adapted for GIS software. Using GeoMedia software the resulting files were added to the GIS workspace for further analysis (Figure 21). There were three sets of information from Arkhangelskoe, Veselovo and Lukhovitsi agricultural areas about crops, yield, responsible organization, amount of nutrients and other statistical information for 2011 - 2015. In some cases the information about particular parcel was contradictory (for example, the attribute Crop was 'wheat' whereas attribute Culture was 'barley' for the same parcel). Sometimes the attribute information was not complete and representatives from the organization

tried to fill it in. If the statistical data were questionable or partially filled, those crop parcels were eliminated from the observation.



Figure 21 Combination of statistical and spatial data

After the review of statistical data regarding to completeness and accuracy, 92 crop parcels were selected for further analysis.

## 4.4 Remote sensing data for cropland area monitoring

Nowadays the observation of crop conditions and area management are top priority issues for agrocompanies. There are many advantages of using remote sensing data and techniques. Contemporary tools of analysis allow farmers derive an up-to date information about crop parcels, provide a real-time crop monitoring and track dynamic particular crop development. For the analysis of agricultural parcels within our case study area the Landsat – 8, Sentinel -2 and RapidEye data were used. Landsat – 8 images were download from the USGS portal (http://earthexplorer.usgs.gov/ ). The data is available on .tiff format and afterwards in ERDAS IMAGINE software the composite image of NIR, Red and Green (5 - 4 - 3) bands were created. These images were used for NDVI index calculation and overgrown areas detection. Sentinel -2 datasets were downloaded from the official European Space Agency portal (Figure 22) (https://scihub.copernicus.eu/dhus/#/home ) and then they were transformed in the SNAP software with a special tool for Sentinel -2 analysis designed by ESA.



Figure 22 ESA portal for Sentinel-2 image search

It is also possible to download the Sentinel -2 data using QGIS software with the python plugin (https://plugins.qgis.org/plugins/ SemiAutomaticClassificationPlugin/) which was designed for automatic and semi-automatic image classification. Besides, it allows users to search and download Sentinel-2 images. However, in our case we have preferred to download data from the official ESA portal because the process of data searching is more convenient. In the portal user can draw a polygon of the area of interest (AOI), whereas in QGIS it is necessary to put exact X,Y coordinates of AOI's vertexes (Figure 23).

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	+++ Multiple R	OI creation	USGS S	pectral Libra	ry 🚮 🌣 Algo	rithm band w	eight 📕	Signature thr	eshold 🛛 😧	Download L	andsat	Download Sentinel
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## Figure 23 QGIS plugin for Sentinel-2 download

The Sentinel-2 images are stored as so called granules which consist of several strips (Figure 24). There is also metadata file which allows to get information about acquisition date, coldness and etc.

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ERDAS APOLLO	I HTML	19.05.2016 15:10	File folder		
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🖳 This PC	INSPIRE INSPIRE	19.05.2016 15:10	XML Document	20 KB	
膧 Desktop	manifest.safe	19.05.2016 15:10	SAFE File	739 KB	
Documents	S2A_OPER_BWI_MSIL1C_PDMC_20160407	19.05.2016 15:10	PNG image	782 KB	
ᠾ Downloads	S2A_OPER_MTD_SAFL1C_PDMC_2016040	19.05.2016 15:10	XML Document	66 KB	
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Figure 24 Sentinel-2 data storage example

Now an average volume of one data set is approximately 6-7 GB which make it difficult to download and manipulate. Before analysis in ERDAS IMAGINE, Sentinel-2 images were pre-processed in SNAP software and the composite image of MidIR, NIR and Red (12 - 8 - 4) was obtained (Figure 25). The resulting image was used for NDWI calculation and wetland areas detection.



Figure 25 Sentinel-2 image transformation in SNAP software

For the analysis and observation of crop condition time series of RapidEye images were used. In cooperation with the experts from Planet organization (<u>https://www.planet.com/</u>) and owner of data – BlackBridge Company, the several datasets were obtained. The data was processed for MCARI index calculation, water and chlorophyll content assessment and image classification.

### 4.4.1 Crop condition assessment

## 4.4.1.1 Overgrown area detection

The issue of overgrown area detection is a priority task in any agrocompany. It is highly important to know how many percent of the company's lands are overgrown since it is mandatory to report about that type of area. Moreover, according to the Russian national law, an organization will be fined if they do not use agricultural areas properly (Federal Law of Russian Federation 2015).

For the overgrown area detection the NDVI index based on Landsat – 8 image was used. Since, according the statistical information, the harvesting was done in September 2015 it was necessary to download the image close to that period. This area is characterized by high level of cloudiness and only one image for the end of September was suitable for the analysis (Figure 26).



Figure 26 Landsat -8 data search for the case study area

Using ERDAS IMAGINE tool for development of spatial model for data processing, the model for overgrown area was developed. It consists of several tools for geospatial processing called operators (Figure 27). The first step of the model is the calculation of NDVI index (as raster input the image with NIR and Red channels should be added), then in cooperation with representatives from agrocompanies, criteria was implemented in order to obtain the thematic image depicting overgrown area. This image afterwards was used for vector dataset creation based on the attribute filter. In this case only values with the NDVI index of 0.4 - 0.8 were vectorized.



Figure 27 Developed model for overgrown area detection

The developed model can be presented as a plain html file and can be edited later on. It includes 1294 rows with description of all steps of the model and each parameters can be adjusted for the particular case.

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<solution td="" xm<=""><td><pre>lns="http://tempuri.org/XMLSchema.xsd"&gt;</pre></td></solution>	<pre>lns="http://tempuri.org/XMLSchema.xsd"&gt;</pre>
<operato< td=""><td>r Namespace="IMAGINE" Name="Process"&gt;</td></operato<>	r Namespace="IMAGINE" Name="Process">
<dis< td=""><td>playName&gt;NDVI Categorised</td></dis<>	playName>NDVI Categorised
<des< td=""><td>cription&gt;Produces a six class dataset based on NDVI values from an input with NIR and Red bands</td></des<>	cription>Produces a six class dataset based on NDVI values from an input with NIR and Red bands
<por< td=""><td>t Name="Port Input 2"&gt;</td></por<>	t Name="Port Input 2">
	<pre><displayname>Output File</displayname></pre>
	<pre><description>Select file name of output categorised NDVI file</description></pre>
	<pre>(Input&gt;true</pre>
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	<pre><optional>false</optional></pre>
	<pre><data></data></pre>
	< <u>StringValue&gt;c:/data/agro/agroosnova/images/landsat_vs_rapideye/june_2015_rapideye_ndvi_re_categor.img</u>
	<type name="File" namespace="IMAGINE"></type>
	<pre>(Attribute Name="AdditionalTypes"&gt;</pre>
	<data></data>
	<pre><stringvalue>{"StringList":["IMAGINE.File"]}</stringvalue></pre>
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	<type name="StringList" namespace="IMAGINE"></type>
	<pre>//Attribute&gt;</pre>
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	STATA 5

Figure 28 Part of the model displayed as script

In order to obtain the map with parcels where the percentage of overgrown area is higher than 60% the GIS tools in GeoMedia softawre for vector analysis were used. And the chain of spatial queries were created. The first step was the vectorization of resulting thematic image to polygons using Complex Polygon Partitioned Boundary output type without border simplification (Figure 29).

Layer name: all_pacrels_ndvi		
Conversion type: Area		
Output type: Complex Polygon Partitioned	Boundary	·
Use value as key: No 👻		
Simplify output feature		
Ihreshold: 5 Meters	Ŧ	
esult feature class		
ature class name: all_pacrels_ndvi_V3		
	OK	Cancel

Figure 29 Vectorization parameters

Then the unique identification (in this case Cadastral number) of parcels was aggregated to the layer with overgrown polygons (Figure 30). This information was used later for the calculation of overgrown area percent from total crop parcel area.

	Aggregat	ion		
Aggregate to summary features in		Output aggregation	as query	
From detail features in	Functional attribute game: XE_number	Output type: Text	Length: 255	Format:
Spatial Aggregation Attribute Aggregation	Expression: FIRST(DetailXE_Number) + · · · / / = • <	<pre> &lt;= &gt; &gt;= AND OR</pre>	NOT LIKE (	<ul> <li>Add</li> <li>Close</li> <li>Undo</li> <li>Paste</li> </ul>
All	<u>Categories:</u> <u>Mani Reamenty Used Functions</u> Operators Constants Date & Time Geometry Logical Math & Trig Math & Trig Mitro Statistical Text View	Eunclions: TREST VALUE MIN MEDUAN MAXX COUNT AVERAGE ABS SQRT STDEV SUM	Attributes: Detail Geom Detail Kol Detail Kul Detail KU Detail XE A Detail XE A Detail XE A Detail XE A Detail Sense. Detail Sense.	etry ∧ tr_Nu troject dverb ва илber илb
	Detail.XE_Number Type of field XE_Number is Text[	50).		

Figure 30 Aggregation query

Then the new attribute with total overgrown area in hectares was created (Figure

31).

Functional attribute name:       Output type:       Format:         Area_h       Double       General Num ▼         Expression:		Functional Attrib	ute	
Expression:  AREA(Input,Geometry; TrueMeas; Hectare)  ABREA(Input,Geometry; TrueMeas; Hectare)  Add  Close  Undo  + * * / = <> < <= > >= AND OR NOT LIKE ( ) Paste  Categories:  Eunctions:  Most Commonly Used Functions All Functions Operators Constants Dete & Time Geometry Logical Mak & Trig Mate Count AREA COUNT AVERAGE ABS Statistical ABS SOB T	Functional attribute <u>n</u> ame: Area_h	Output type: Double	Format: General Num 💌	
AREA(Input,Geometry; TrueMeas; Hectare)       Add         Close       Undo         + · * / = <> < <= >>= AND OR NOT LIKE ( ) Paste         Categories:       Eunctions:         Most Commonly Used Functions       AREA         Operators       VALUE         Constants       MAX         Cooling       MAX         Count       AVERAGE         Math & Trig       AVERAGE         Misc       SOBIT	<u>E</u> xpression:			
Close         Undo         +       ·       /       =       >>=       AND       OR       NOT       LIKE       (       )       Paste         Categories:       Eunctions:       Eunctions:       Attributes:       Attributes:         Most Commonly Used Functions       FIRST       AREA       Not LIKE       (       )       Paste         Operators       Operators       VALUE       NMN       Not XE_number       Input Seometry         Constants       MAX       COUNT       MAX       COUNT       AS         Misc       ABS       SOBT       SOBT       SOBT	AREA(Input,Geometry; TrueMeas; I	Hectare)	<u> </u>	A <u>d</u> d
Line     Image: Second s				Close
Undo           + · * /         = <> < <= > >=         AND         OR         NOT         LIKE         ( )         Paste           Categories:         Eunctions:         Attributes:         Input. Geometry         Input.XE_number           All Functions         FIRST         AREA         Input.XE_number         Input.XE_number           Operators         VALUE         MIN         MEDIAN         Geometry         Input.XE_number           Geometry         MAX         COUNT         ABS         SOBRT         SOBRT         Input.Second				-1-1-1
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Categories:         Eunctions:         Attributes:           Most Commonly Used Functions         FIRST         Input. Geometry           All Functions         AREA         Input. Geometry           Operators         VALUE         Input.XE_number           Constants         MIN         Most Commonly           Date & Time         MEDIAN         Geometry           Logical         COUNT         MAS           Misc         ABS         SOBIT	+ · × / = ◇ <	<= > >= AND OR	NOT LIKE ( )	Paste
Most Commonly Used Functions         FIRST         Input.Geometry           All Functions         AREA         Input.Seometry           Operators         VALUE         Input.XE_number           Constants         MIN         Date & Time         MEDIAN           Geometry         MAX         Logical         COUNT           Mate & Trig         AVERAGE         ABS           Statistical         SOBIT         SOBIT	<u>C</u> ategories:	Eunctions:	<u>Attributes:</u>	
Text STDEV View SUM	Most Commonly Used Functions All Functions Operators Constants Date & Time Geometry Logical Math & Trig Misc Statistical Text View	FIRST AREA VALUE MIN MEDIAN MAX COUNT AVERAGE ABS SQRT STDEV SUM	Input.Geometry Input.XE_number	

Figure 31 Overgrown area calculation

Using the calculated information about overgrown area of total area of crop parcels,

the percent of uncultivated area was obtained (Figure 32).

	Functional Attribute		×
Functional attribute <u>n</u> ame: Percent_of_overgrown	Output type: Double	Format: General Num 💌	
Expression:  Dutput.Area_h*100/Input.Parcel_4	area	<u>^</u>	OK
			Cancel
+ - × / = < <	<= > >= AND OR NO	)T LIKE ( )	<u>U</u> ndo <u>P</u> aste
Categories:	Eunctions:	Attributes:	
Most Commonly Used Functions All Functions Operators Date & Time Geometry Logical Math & Trig Misc Statistical Text View	FIRST AREA VALUE MIN MEDIAN MAX COUNT AVERAGE ABS SQRT STDEV SUM	Input.Geometry Input.Parcel_area Input.XE_number Output.Area_h Output.Percent_ol	f_overgrown

Figure 32 Calculation of overgrown area percentage

In order to obtain the map depicting parcels with the percentage of overgrown higher than 60%, the attribute filter was applied (Figure 33).

Аttributes: Правой_статус Примечания Процент_зарастания Тип_участка Частично_обрабатываемые_ < Ш >	Operators:           =         >=         <=           <>>         <         <           ()         and         or	<u>Show Value</u>
 Filter: Процент_зарастания >= 60		



The resulting map of overgrown areas were combined with statistical information and added as additional attribute to the existing vector file (Figure 34).



Figure 34 Resulting vector file with the percent of overgrown area

## 4.4.1.2 Water content

Monitoring of the hydromorphic conditions of croplands is an essential process in agricultural monitoring. For better planning of crop planting and irrigative system development, it is necessary to get information about water content in plants. For the detection areas with a water stress, the NDWI index was calculated using Sentinel – 2 image. The satellite was launched in 2015 and images for our case study area are available since November, 2015. It is more reasonable to calculate the index during the second decade after the planting (Gao 1996), but since there was no data available for the June, the image captured on May, 2016 was used. Using ERDAS IMAGINE tool for indices calculation, the map with the areas characterized by highest and lowest level of water content was developed (Figure 35).



Figure 35 Water content map

## 4.4.1.3 Chlorophyll content

For the assessment of chlorophyll content the MCARI index was calculated based on time series of RapidEye data. Using time series data it is possible to track the changes in chlorophyll content and identify areas with a deficit of nitrogen in the vegetation canopy. In our case we had two images captured on May and June, 2016 for parcels where sowing was made in the beginning of May. The vegetation index was calculated in ERDAS IMAGINE using spatial model tool and resulting thematic image depicts the relative chlorophyll content in vegetation canopy. (Figure 36).



Figure 36 MCARI index calculation as a spatial model

Using two datasets of chlorophyll content it is possible to observe the changes in nutrients over the weeks and distinguish area where the plant growth process is disrupted (Figure 37).



Figure 37 Relative chlorophyll maps. May and June, 2016

In order to obtain the information about crop parcels the fusion of two thematic images has been accomplished. Eventually, the final model for crop parcels with the plant growth disturbance identification was developed. That process consists of chlorophyll content in plants' leaves estimation through MCARI index calculation and thematic classification, water content assessment calculating NDWI index and classification and then combination of two thematic images using intersection operator. As a result the image the map depicting problematic crop areas (Figure 38).



### 4.4.2 Verification of statistical information

In our case unsupervised classification based on the RapidEye image (June, 2015) was fulfilled for image classification and further verification. In the most cases the classes of pixels (yellow) grouped well and matched with the crop polygons from agrocompany (red contour) (Figure 39).



Figure 39 Results of unsupervised classification

However, some discrepancy has been found when the classification and statistical information about crop type did not correspond. According to the results of image classification the field displayed in the figure below mainly has two crops, yet only one type (wheat) is indicated in the statistical information (Figure 40).



Figure 40 Crop parcel with two crop types

After correspondence with local farmers it was revealed that it is not the inaccuracy of the classification process. The representatives of agrocompany confirmed that in 2015 they did not have enough wheat seed and this particular field has been partially covered by barley.

# 5. Implications for food security

Croplands monitoring is highly important issue in maintaining sustainable agriculture and food security. Through remote sensing data analysis such as vegetation indices calculation the maps with problematic crop parcels can be derived. Coupled with the statistical information combined in GIS software results can be verified and improved.

Information about overgrown area which was derived through the analysis of vegetation index has revealed that the total area of overgrown lands is 10.48 sq.km (20,5%). There are 23 parcels out of 91 which are characterized by high level of overgrowing (>60%) (Figure 41).



Figure 41 Overgrown crop parcels

For detection parcels requiring farmers' attention, the combination of water stress information and chlorophyll content was used. The final map represents the problematic or dysfunctional crop areas where lack of liquid or nutrients was observed (Figure 42).



## Figure 42 Parcels with disturbance of growing process

Using the classified images and statistical data, 13 parcels with mismatching information have been found. Information about crop type of all parcels have been checked with the representatives from agrcompany and farmers. In 7 cases they

confirmed that they indicated planned crop type even if parcels were covered by another crop. It was not possible to check contradicted information about crop type of 5 crop parcels since there was no confirmation from the local farmers and the additional field trip for that parcels is required.

The results acquired during this research can be used by agroholdings and local farmers for monitoring of agricultural area. The detection of diseases and fields with stressed plants at early stages helps farmers and stakeholders save their budget minimizing efforts needed for elimination of negative consequences. If proper treatments such as application of fertilizers or irrigation were not introduced in the right time, delay in plant growth can reduce the potential final yield. The spatial models which have been developed within this research for automatic satellite data processing allow to obtain all necessary information for identification of crop parcels requiring farmers' attention. Moreover, the settings in developed models can be modified in order to fit requirement for particular need of agrocompany. Thus, the developed algorithm could be easily replicated at any other farming site in other regions.

Further assessment using more detailed information about crops will improve an accuracy of detecting overgrown areas and parcels with stressed crops. More indices which characterize amount of nutrients can be taken into account and their calculation can be added to the existing models. Taking into account that in a few cases statistical information did not correspond with a real situation on the field, additional field trips are required. All in all, the further development of the models using other indices or data sources will provide better and up-to-date results. Moreover, there are many other ways to use obtained satellite images and developed models as a basis for future research. For example, images captured every decade during the year providing spectral information of particular area in different stages of crop development (from

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bare ground to harvest) can be used for crop type identification and measurements of deviation from the normal growth process. Also in case of historical data about yield is available it will be possible to estimate current yield and make prediction for future yields.

## 6. Conclusions

The principal aim of this research was to investigate potential application of remote sensing data, GIS and spatial modelling techniques for agricultural monitoring and food security assessment. During the research the application of the most commonly used and publicly accessible free data (Sentinel-2 and Landsat-8) and commercial images (RapidEye) have been assessed for defining crop health and supporting agricultural monitoring.

Several parameters of crop condition and vegetation health have been analyzed. Analysis of overgrown area requires information about condition of vegetation canopy for a certain period of time. By using Landsat-8 and NDVI index the uncultivated parcels or area covered with shrubs and bushes were identified. Another acute issue for farmers is the detection of crop parcels where process of plant growth is disrupted. The information about problematic areas was obtained through water and chlorophyll content assessment based on Sentinel-2 and RapidEye series of images for different time periods.

The another way of remote sensing data and GIS techniques usage is the updating of statistical information. By using GIS clustering tools and image classification techniques the possibility of statistics correction and updating was achieved. The final classified image was used for analysis regarding the correspondence statistical information to the information derived from satellite images. There were several cases of discrepancy when information about crop type of the particular parcel had only one value, whereas there were two classes on classified images. In most cases, the local farmers confirmed that they used two types of seeds and the statistical information for those parcels were updated based on remote sensing data.

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All types of analysis and data processing was assembled in the spatial model. The spatial model developed through this research allows problematic parcels to be identified. The model could be used for an assessment of various crop conditions and it can be replicated at other farming sites within the region and worldwide. The developed algorithm combines raster, vector and statistical data providing comprehensive picture of current situation on the field.

The results obtained through the spatial model executing can minimize the risk of crop failure and reduce the cost of negative consequences elimination. The identification of problematic areas of cropland requiring attention and intervention of farm management at early stages can increase crop yields and ensure sustainable agriculture. All mentioned examples of remote sensing data analysis showed the high potential of contemporary GIS and satellite techniques to contribute to maintaining sustainable agriculture and ensure food security.

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