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# Analysis of atmospheric $CO_2$ concentration variations by using spectral indexes: Ukrainian case study

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## Foreword

This report summarizes the results of the research project conducted during the 2011 Young Scientists Summer Program with Advanced System Analysis Program at the International Institute of Applied Systems Analysis, Laxenburg, Austria. The main focus of the research is on using spectral data and measurements received from remote sensing for the analysis of vegetation systems by using spectral indices, in particular, analysis of the dependencies between carbon fluxes and atmospheric $CO_2$ concentration; analysis of inherent uncertainties in spectral data.

The long-term goal of the research is to enhance the control of emissions for efficient and environmentally safe emissions exchanges and trading among countries using remote sensing: it is important to track the dynamics of $CO_2$ concentration in the atmosphere before and after emissions exchange and market operations.

## Abstract

The objective of these studies is to analyze the possibility of determining $CO_2$ concentration in the atmosphere by using spectral indexes—Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI) and GPP, PsnNet. In the studies, spatially explicit NDVI and EVI values at a resolution of 1km were calculated for two years, 2009 and 2010, and used for the analysis of dependencies between plant biomass growth and environmental conditions — $CO_2$ concentration in the atmosphere, temperature, precipitation, and time of the year. For every spatial point, the value of photosynthesis activity was calculated and the relationships among the $CO_2$ exchanges, the remotely sensed Normalized Difference Vegetation Index (NDVI), and other environmental factors were examined using the Pearson correlation coefficient. These studies explore the relationship between MODIS products, i.e., Normalized Difference Vegetation Index, Enhanced Vegetation Index, gross primary productivity, net Photosynthesis, and $CO_2$ concentration derived from GOSAT satellite.

These measurements could maximize the utility of expensive flux towers for evaluating various carbon management strategies, carbon certification, quotas verification, validation and calibration of carbon flux models and can supplement data base. Also understanding how increasing concentration to improve plant growth can help to calculate biomass potential in $CO_2$ accumulation.

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## About the author

Mar’yana graduated from the National University of “Kyiv-Mohyla Academy” in 2008. She specializes in Ecology and Environmental Protection. She is currently a second year PhD student at the National Centre of the Aerospace Research of the Earth IGS, NAS Ukraine. She started her research career in 2003 with investigating the land reclamation topic; she was also a participant of the UNEP project “Oil Spill in the Kerch Strait”. Her current research interests are: benefits of ecosystems, climate change adaptation and stabilities of ecosystems.

## List of Acronyms

AOD — Aerosol Optical Depth

AVHRR — Advanced Very High Resolution Radiometer

EVI — Enhanced Vegetation Index

GOSAT — Greenhouse Gas Observing Satellite

GPP — Gross Primary Production

HDF — Hierarchical Data Format

LST — Land Surface Temperature

MODIS — Resolution Imaging Spectroradiometer

NDVI — Normalized Difference Vegetation Index

NOAA — the US National Oceanic Atmospheric Administration

PsnNet — Net Photosynthesis

# Analysis of atmospheric $CO_2$ concentration variations by using spectral indexes: Ukrainian case study

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## Introduction

Rising $CO_2$ concentration in the atmosphere speeds up the process of photosynthesis in plants. There are many studies supporting this fact, for example, laboratory experiments (Norby et al., 2002) show that $CO_2$ enrichment increases productivity of a closed-canopy deciduous forest. Lim et al. (2004) summarizes substantial knowledge from controlled experiments of DeLucia et al., 1999 and Körner 2000 that elevated $CO_2$ will stimulate future terrestrial photosynthesis. In such experiments, net primary production often increases by 30% or more in response to a doubling of the atmospheric $CO_2$ concentration.

As the vegetation assimilates $CO_2$ from the atmosphere, the rate of change in the atmospheric $CO_2$ concentration tracks the rate of change in the amount of foliage (Keeling et al., 1996). When there is a large increase in foliage, the vegetation will consume more $CO_2$ from the atmosphere, and a relatively large decrease in atmospheric $CO_2$ concentration will follow. Hence, changes in $CO_2$ concentration driven by changes in vegetation growth are expected to produce a negative correlation between NDVI change in a given month and $CO_2$ concentration change in the following month (Lim et al., 2004).

Such a correlation can be interpreted as the influence of vegetation development on the atmospheric $CO_2$ concentration. On the other hand, if a change in atmospheric $CO_2$ in a given month precedes a change in NDVI the following month, and the correlation is positive, this will suggest (but not prove) a possible $CO_2$ fertilization effect (Lim et al., 2004).

The objective of this study is to evaluate how spectral indexes and other relevant GIS data can be used for determining the changes (increase or decrease) of the $CO_2$ concentration in the atmosphere. Analysis of the land cover state in a concrete point and of the atmospheric $CO_2$ concentration over this point not only increases the accuracy of conclusions but also provides completeness of the data in each point of the case study region. In the study the following data describing the ecosystems state were used: photosynthetic active radiation, Normalized Difference Vegetation Index, Enhanced Vegetation Index, Gross Primary Production, Net Photosynthesis, and information about meteorological conditions—Surface Temperature. The relationship between the $CO_2$ exchange, NDVI, EVI, and other environmental factors were examined in the period from March 2009 to October 2010.

The goal is to investigate how temperature, precipitation, and atmospheric $CO_2$ concentration influence photosynthesis activity. We estimate the dependence between $CO_2$ concentration and ecosystem biomass deriving correlation coefficients between vegetation indexes, GPP, NPP and photosynthesis activity for each point in a concrete period of the year and average for some months.

The studies cover territories of Rivnenska and Zhutomurska oblasts in Ukraine. These two neighboring regions have similar meteorological conditions and land cover types. The dominant land cover types are croplands, pine and deciduous forests. Trees are generally more responsive to $CO_2$ changes than grass, forbs, legumes and crops, showing an average 47% stimulation in light-saturated $CO_2$ uptake, that's why we analyze areas with the presence of forests (Elizabeth et. al., 2005). Another important land use type investigated is arable land as it covers most of the Ukrainian territory. The available GIS data is often incomplete and may contain observation errors. To fill data gaps and eliminate errors and uncertainties, robust downscaling and upscaling algorithms described in (Fischer, Ermoliev, et al., 2006) were adjusted to fulfill the needs of these studies.

The analysis of dependencies between plants reaction to $CO_2$ changes will help improve land management strategies for optimizing carbon accumulation.

# 1. Model characteristic

## 1.1. Pierson Correlation Coefficient

In R. K. Kaufmann et al. (2008), authors analyzed the relationship between station measurements of atmospheric carbon dioxide, satellite measurements of NDVI, anthropogenic carbon emissions, and aerosol optical depth using the notion of Granger causality. The statistical methodology proceeds in three steps. In the first step, authors estimate a vector autoregression in which NDVI and the atmospheric concentration of carbon dioxide are endogenous variables. In the second step, they test for Granger causality by calculating a test statistic to evaluate a restriction that eliminates lagged values of the potentially causal variable. Values of the test statistic that reject this restriction identify months when and locations where there is a causal relationship between atmospheric $CO_2$ and NDVI. A third step repeats this procedure with NDVI data at different spatial resolutions to ensure that the results are robust.

The methodology compiles monthly data for NDVI, atmospheric carbon dioxide, and annual data for anthropogenic carbon emissions. However, this research used the method described in Lim et at. (2004).

In Lim et al. (2004) authors analyze the correlation between $CO_2$ and NDVI by using Pearson product-moment coefficient of correlation. The Pearson product-moment correlation coefficient is a measure of the correlation (linear dependence) between two variables *X* and *Y*, giving a value between +1 and −1 inclusive. It is widely used as a measure of the strength of linear dependence between two variables. The calculation of the correlation coefficient incorporates the errors of the 2 measurements, NDVI and atmospheric $CO_2$ concentration. Both atmospheric $CO_2$ concentration and NDVI are time-dependent variables. For this reason it is important to analyze these two characteristics in the same period of time.

## 1.2. Input data

In these studies, the following independent data were used which came from the satellite measurements: the $CO_2$ concentration came from Japanese satellite GOSAT; Net Photosynthesis, Net Primary Production, and Surface temperature, NDVI, EVI - from MODIS (Moderate Resolution Imaging Spectroradiometer), which is a key instrument on board the Terra\ASTER satellite. The global land cover map (2005) was also prepared based on satellite data.

The Greenhouse gases Observing SATellite (GOSAT) is designed to monitor the global distribution of carbon dioxide ($CO_2$) from the orbit. The satellite was launched in 2008, therefore, it permits investigating data for vegetation periods during 2009 and 2010 years.

GOSAT observes infrared light reflected and emitted from the earth's surface and the atmosphere. Column abundances of $CO_2$ and $CH_4$ are calculated from the observational data. The column abundance of a gas species is expressed as the number of the gas molecules in a column above a unit surface area. GOSAT completes one revolution in about 100 minutes and the satellite returns to the same point in space in three days.

The observation instrument onboard the satellite is the Thermal and Near-infrared Sensor for carbon Observation (TANSO). TANSO is composed of two subunits: the Fourier Transform Spectrometer (FTS) and the Cloud and Aerosol Imager (CAI). Over the three-day period, FTS takes fifty-six thousand measurements, covering the entire globe. Since the analysis is limited to areas under clear sky conditions, only two to five percent of the data collected are usable for calculating column abundances of $CO_2$. Nevertheless, the number of data point significantly surpasses the current number of ground monitoring stations, which is below 200 (GOSAT instruments and observational methods).

Main mission sensor of the GOSAT is a Fourier Transform Spectrometer with high optical throughput, spectral resolution and wide spectral coverage, and a cloud-aerosol detecting imager attached to the satellite.

The targets of the GOSAT mission are to conduct observation of $CO_2$ density with 1% (4ppmv) relative accuracy over a 3-month average in sub-continental spatial resolution during the first commitment period (2008 to 2012) of the Kyoto Protocol, and to reduce errors by half in identifying the GHGs source and sink in Sub-continental scale using the data obtained by the GOSAT in conjunction with the data gathered by the ground instruments (Hamazaki et al., 2004).

The data coming from GOSAT provide unprecedented geographic coverage of column averaged $CO_2$ concentrations (Alexandrov, Matsunaga, in press).

The GOSAT data on daily $xCO_2$ are provided as a set of HDF files. Each file contains information about the coordinates of the points of observations, observed values, and some additional information. The $xCO_2$[1] values are lower than [$CO_2$] values by 9 ppm on average. The function Xoffset determines the optimal offset for each meridian, which is defined as an offset that reduce the difference between $xCO_2$ and [$CO_2$] at the edges of latitudinal belt covered by GOSAT observations (Alexandrov, Matsunaga in press).

The data come from GOSAT product it is the column $CO_2$ concentration for concrete point with indicated latitude, longitude coordinates. Part of this product includes the data that is determined by performing temporal and space interpolation on GPV data provided by the Meteorological Agency. The L2 $CO_2$ column abundance data is provided in an HDF5-formatted file (NIES GOSAT Product Format Descriptions).

In summary, the following data can be derived from GOSAT:

- $CO_2$ column abundance;
- $CO_2$ column abundance error;
- $CO_2$ volume mixing ratio;
- observed position;
- observation altitude;
- solar zenith/azimuth angle;

[1] $xCO_2$ is the ratio of the total number of $CO_2$ molecules against that of dry air molecules, not only in the neighborhood of the Earth's surface, but in the total vertical column up to the top of the atmosphere (Brief explanation on FTS SWIR Level 2 $CO_2$ and CH4 Column Abundance Products).

- satellite zenith/azimuth angle;
- satellite attitude;
- satellite position;
- ocean/land flag (NIES GOSAT Product Format Descriptions).

This research uses Level 2 of the GOSAT product, versions 00.50, 00.80, 00.90, 01.10, 01.20, 01.30. Only “cloud-free” data are selected, other basic factors in data selection such as quality of signal and ground surface roughness are also checked. The validation results can be found in the document “Summary of the GOSAT Level 2 Data Product Validation Activity”, which is available online at the GOSAT User Interface Gateway.

The version 00.50 of the GOSAT Level 2 data product (column-averaged volume mixing ratios of Carbon Dioxide ($xCO_2$) were compared against reference data obtained with ground-based high-resolution Fourier transform spectrometer and instruments onboard the aircrafts participating in the CONTRAIL (Comprehensive Observation Network for Trace gases by AirLinen) project and the NOAA’s airborne measurement program.

The precision of the ground-based FTS in measuring $xCO_2$ under clear-sky and partially-clouded sky is approximately 0.1%. Through calibrating these instruments with in-situ airborne measurement data, the uncertainty of xCO2 associated with the ground-based FTS measurement was determinated to be 0.3% (1 ppm). The uncertainty associated with the airborne $CO_2$ measurements is 0.2ppm. The values of $xCO_2$ derived with the airborne observation data have uncertainty values of ~1ppm (common remarks on the FTS SWIR Level 2 Data Product for all months).

Results of the validation activity show that TANSO-FTS Level 2 column-average data $xCO_2$ was lower by 2-3%. The standard deviations of the Level 2 $xCO_2$ (one sigma) were larger than those of the reference values. The zonal means of the Level 2 $xCO_2$ was broadly consistent with those of the reference value.

The version 01.xx of the GOSAT Level 2 data (column-averaged volume mixing ratios of Carbon Dioxide ($xCO_2$) were compared to the same type of data in the version 00.50. The results show that under the conditions of the precision of the ground-based FTS in measuring under clear-sky and partially-clouded sky is approximately 0.1%. Through calibrating these instruments with in-situ airborne measurement data, the uncertainty of $xCO_2$ associated with the ground-based FTS measurement were determinate to be ~0.8ppm. The uncertainty associated with the airborne $CO_2$ measurements is 0.2ppm. The values of $xCO_2$ derived from the airborne observation data have an uncertainty value of ~1ppm. This large uncertainty of the $xCO_2$ results from the concentrations assumed at altitudes where the airborne measurements were not taken (common remarks on the FTS SWIR Level 2 Data Product for all months). For now (September 2011), only 2 validation documents from the GOSAT user interface gateway are available.

Ukraine consists of 24 regions and the Crimea. The case study covers the territory of two regions - Rivnensky and Zhutomyrsky. These two neighboring regions have similar type of vegetation and meteorological conditions. Dominant types of land cover are forest and cropland.

Information about Net Photosynthesis, Net Primary Production, spectral indexes (Normalized different vegetation index, enhanced vegetation index), and surface temperature are derived from MODIS data. Characteristics of the data are reflected in Table 1. MODIS is a key instrument aboard the Terra (EOS AM) and Aqua (EOS PM) satellites. Terra's orbit around the Earth is timed so that it passes from north to south across the equator in the morning. Terra MODIS and Aqua MODIS are viewing the entire Earth's surface every 1 to 2 days, acquiring data in 36 spectral bands, or groups of wavelengths (about MODIS).

**Table 1.** Characteristics of the MODIS data

| # | Short name | MODIS product | Spatial resolution, m | Temporal resolution, days |
|---|---|---|---|---|
| 1 | MOD11A2 | Daytime 1km grid land surface temperature | 1000 | 8 |
| 2 | MOD13A2 | Vegetation indexes:<br>Normalized Difference Vegetation Index,<br>Enhanced Vegetation Index | 1000 | 16 |
| 3 | MOD17A2 | Gross Primary Productivity, Net Photosynthesis | 1000 | 8 |

The Land Surface Temperature (LST) 8-day data are composed of the daily 1-kilometer LST MODIS product MOD11A2and stored on a 1-km Sinusoidal grid as the average values of clear-sky LSTs during an 8-day period.

The MODIS Normalized Difference Vegetation Index complements NOAA's Advanced Very High Resolution Radiometer (AVHRR) NDVI products and provides continuity for time series historical applications. MODIS also includes a new Enhanced Vegetation Index that minimizes canopy background variations and maintains sensitivity over dense vegetation conditions. The EVI also uses the blue band to remove residual atmosphere contamination caused by smoke and sub-pixel thin-cloud clouds. The MODIS NDVI and EVI products are computed from atmospherically corrected bi-directional surface reflectance that have been masked for water, clouds, heavy aerosols, and cloud shadows.

Global MOD13A2 data are provided every 16 days at 1-kilometer spatial resolution as a gridded level-3 product in the Sinusoidal projection. MOD17 product produces gross primary production of vegetation every day, and sums to net primary production, essentially vegetation growth, at the end of the year. These variables provide the initial calculation for growing season and carbon cycle analysis. The Gross Primary Production product is designed to provide an accurate regular measure of the growth of the terrestrial vegetation. Production is determined by first computing a daily net photosynthesis value which is then composited over an 8-day interval of observations for a year.

The product is a cumulative composite of GPP values based on the radiation use efficiency concept that may be used as inputs to data models for calculating terrestrial energy, carbon, water cycle processes, and biogeochemistry of vegetation and are used for agriculture, range and forest production estimates. Collection 5 of the MODIS data was used. It commenced in mid-2006, and is the current version of the MODIS product (Giglio, 2010).

For classifying the type of ecosystems the Globcover land cover product was used which is global land cover map produced for the period December 2004 – June 2006. The main land cover classes for research points in our territory are:

- Rainfed croplands;
- Mosaic croplands (50-70%)/vegetation (grassland/shrubland/forest) (20-50%);
- Closed (>40%) broadleaved deciduous forest (>5m);
- Mosaic vegetation (grassland/shrubland/forest) (50-70%)/cropland (20-50%);
- Closed to open (>15%) mixed broadleaved and needleleaved forest (>5m);
- Mosaic forest or shrubland (50-70%)/grassland (20-50%).

## 1.3. Uncertainties of the input data

From web publications (e.g. MODIS Land Team Validation) we can see that the MOD11 Collection 5 (C5) products have been validated at Stage 2 via a series of field campaigns conducted in 2000-2007, and over more locations and time periods through radiance-based validation studies. Accuracy is better than 1K (0.5K in most cases), as expected pre-launch.

Validation at stage 3 has been achieved for the MODIS Vegetation Index product (MOD13). Accuracy is within ±0.025, which represents the ability of the 16-day VI products to retrieve a top of canopy and nadir vegetation index value using high quality results (clear, low aerosol, sensor view angle < 30 degrees). This estimate is based on comparisons with AERONET-corrected data over a range of biomes and seasonality. The normalized difference vegetation index accuracy is within ±0.025, while that of the enhanced vegetation index is within ±0.015, and the accuracy of retrieving top of canopy vegetation index for a good quality day (high quality without the nadir view requirement) would be to within ±0.020 for NDVI and ±0.010 for EVI. Errors in the red band associated with residual atmospheric effects are the main source of the NDVI errors. The blue band is helpful to correct the red band bias and reduce errors in EVI (MODIS Land Team Validation. Status for: Vegetation Indices (MOD13)).

Analyses from various airborne and field validation campaigns demonstrate that over most biomes, MODIS near-nadir satellite vegetation index values have very good agreement with top-of-canopy nadir vegetation index and with land surface biophysical properties. Comparisons of seasonal MODIS vegetation index with seasonal flux tower measurements of gross primary production show very strong agreement across a global set of biome types. MODIS vegetation index values have also been found to be in good agreement with vegetation index computed from the MODIS Nadir BRDF-Adjusted Reflectance product, 8-day surface reflectance, as well as with vegetation indexes generated from the ASTER and Landsat ETM+ sensors (MODIS Land Team Validation. Status for: Vegetation Indices (MOD13)).

Validation for MOD 17 Product version, Collection 5 has not been achieved yet. Bicheron (2008) shows land cover validation results, describes methodology, sampling strategy, reference dataset for validation of Global Land Cover map, which was used for detection type of land cover. The quality of the Global Land Cover product is highly dependent on the reference land cover database used for the labeling process and on the number of valid observations available as input. When the reference dataset is of higher spatial resolution with a high thematic detail, the Global Land Cover product also shows a high accuracy. The results show that the accuracy level found is about 67.10%. The overall accuracy weighted by the type of area reaches 73% using 3167 points globally distributed and including homogeneous and heterogeneous landscapes (Bicheron, 2008).

To increase this rate, we can use a method proposed in (Fischer, Ermoliev et al., 2006). Available satellite GIS data may often be incomplete and contain observation errors. To fill data gaps and eliminate some of the errors and uncertainties, robust downscaling and upscaling algorithms described in (Fischer, Ermoliev et al., 2006) were adjusted to fulfill the needs of these studies.

## 2. Effects of $CO_2$ concentration on plant growth

The dependency of the photosynthesis intensity from environmental factors and season of the year we can calculate using Libieg principle of the limiting factors. Photosynthesis process is described in this model by using flow of the Carbon from atmosphere to the ecosystem. The levels of this flow are a function of the average monthly level of $CO_2$ concentration (*C*) in the atmosphere, temperature (*T*), precipitation (*P*), and depend on time (*t*). From the law of limiting factors (Libieg principle) function of the four factors which have input on the Carbon flow we can write as:

$$f(C,T,P,t) = \min\left[h(CO_2), g(T)\right] q(P) x(t). \qquad (1)$$

The dependency between the flow of carbon and the carbon dioxide in the atmosphere is captured by the following relation:

$$h(CO_2) = 1 + \mathrm{Z}\beta \ln\left(\frac{C}{350}\right) \qquad (2)$$

where,

*Z*—conversion factor from “one plant” level to ecosystem level (for area with dominant cropland or broadleaved deciduous forest or mosaic forest *Z=0,6*);

*β*—growth factor (for area with dominant cropland *β=0,57;* for areas with dominant broadleaved deciduous forest or areas with dominant mosaic forest *β =0,71*);

350—averadge concentration $CO_2$ in the atmosphere in XX century.

The relation between carbon flow and temperature (T):

$$g(T) = 1{,}2\exp\left[-0.0117(T - T_{opt})^2\right] \qquad (3)$$

where,

$T_{opt}$ —optimum temperature for photosynthesis (for area with dominant cropland $T_{opt}$ *=20°C;* for areas with dominant broadleaved deciduous forest or areas with dominant mosaic forest $T_{opt}$ *=17°C*);

The relation between the carbon flow and precipitation (P)[2]:

$$g(P) = 1 - \exp(-k_p P) \tag{4}$$

where,

$k_p$ – coefficient, which show photosynthesis sensitivity of the ecosystems from precipitations ($k_p$ *=0,075)*;

The relation between the carbon flow in different periods (*t*) of the year:

$$x(t) = 1 - \left[\sin(\pi t - \varphi_{ph} \cdot \pi)\right]^s \tag{5}$$

where,

$\varphi_{ph}$ —coefficient, which show a place on the timeline (for areas with dominant cropland $\varphi_{ph}$ *=0,25;* for areas with dominant broadleaved deciduous forest or areas with dominant mosaic forest $\varphi_{ph}$ *=0,33*[3]*)*;

s—determines the steepness (for areas with dominant cropland *s=4;* for areas with dominant broadleaved deciduous forest or areas with dominant mosaic forest *s=16).*

# 3. Reaction of the indexes

## 3.1 Reaction of the vegetation indexes

The Normalized Difference Vegetation Index provides a measure of the amount and vigor of vegetation at the land surface. The magnitude of NDVI is related to the level of photosynthetic activity in the observed vegetation. In general, higher values of NDVI indicate greater vigor and amounts of vegetation. Normalized Difference Vegetation Index is a reliable index for describing the surface vegetation greenness, which reflects the condition of the biomass in a given area (Asrar et al., 1992) (Lim et al., 2004). It calculates as (Rouse et al., 1973):

$$NDVI = (R_{NIR} - R_{RED})/(R_{NIR} + R_{RED}) \tag{6}$$

where,

$R_{NIR}$ and $R_{RED}$ are reflectance's in the near-infrared and red spectral bands, respectively.

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[2] In Ukraine precipitations are not the limiting factor, so q(P)=0,95 for all types of the ecosystems.

[3] All coefficients are from Bun et al. 2004

NDVI is a nonlinear function that varies between -1 and +1 (undefined when NIR and VIS are zero). Values of NDVI for vegetated land generally range from about 0.1 to 0.7, with values greater than 0.5 indicating dense vegetation.

Many of the conditions that favorably or adversely affect plant development result in a corresponding increase or reduction of the photosynthetically active biomass and this response can often be captured though spectral measures such as NDVI (Tucker, 1979). During the past 25-35 years, the NDVI has been widely used for vegetation mapping and monitoring land-cover change in different regions of the Earth. A search depending between NDVI value and $CO_2$ concentration in the atmosphere by using Pearson correlation coefficient will show which type of influence is in every concrete situation. For the research territory, NDVI values were extracted for the growing season 2009 and 2010 .

The possibility that rising atmospheric $CO_2$ concentrations are influencing plant growth in contemporary ecosystems was analysed by (Lim et al. 2004). The studies have been done on a small spatial scale. The authors correlated the monthly rate of relative change in normalized difference vegetation index, with the rate of change in atmospheric $CO_2$ concentration during the natural vegetation growing season within three different eco-region zones of North America over the period 1982-1992, after which they explored the temporal progression of annual minimum NDVI over the period 1982-2001 throughout the eastern humid temperate zone of North America.

The results (Lim et al., 2004) show relatively high and positive correlation coefficients when the monthly rate of change in NDVI was 1 mo lagged to that for $CO_2$. Authors underscore that these results suggest, but do not prove, a $CO_2$ fertilization effect on natural vegetation development. The correlation coefficients changed from relatively high and positive correlations when NDVI was lagged 1 mo behind $CO_2$ to relatively high and negative correlations when $CO_2$ was lagged 1 mo behind NDVI. The correlation coefficients changed from relatively high and positive correlations when NDVI was lagged 1 mo behind $CO_2$ to relatively high and negative correlations when $CO_2$ was lagged 1 mo behind NDVI. A general increase in the annual maximum greenness of the vegetation was also found in most of the regions studied from 1982 to 2001. The results of this study are generally consistent with the notion of a contemporary $CO_2$ fertilization effect. With the analysis of NDVI derived from advanced very high resolution radiometer (AVHRR) data, Lim illustrates that $CO_2$ was positively correlated with the rate of change in vegetation greenness in the following month, and in most experiments the correlation was high.

In Tagir G. Gilmanov et al., 2005, the authors show the advantages and pitfalls of using NDVI. Yoder & Waring (1994) and Gamon et al. (1993) identify NDVI as quantifying potential photosynthetic activity or an indicator of physiological change at the canopy level. NDVI became the vegetation index most widely used in the context of ecosystem studies because it was shown to be closely related to biomass (Wylie et al., 2002; Boelman et al., 2003), biomass moisture (Chladil & Nuñez, 1995), leaf area index (Gower et al., 1999), absorbtion of photosynthetically active radiation (Hall et al., 1995; Gower et al., 1999), trends of photosynthesis and transpiration (Running & Nemani, 1988; Slayback et al., 2003), respiration (Boelman et al., 2003) and $CO_2$ uptake (Frank & Karn, 2003). On the other hand, NDVI has been shown to be sensitive to view angle effects (Epiphanio & Huete, 1995), standing dead or litter biomass (Huete & Jackson, 1987), saturation at high LAI (Gao et al., 2000), and soil and atmospheric effects".

In the work "The Power of Monitoring Stations and a $CO_2$ Fertilization Effect: Evidence from Causal Relationships between NDVI and Carbon Dioxide" (Kaufmann et al., 2008) authors propose a hypothesis which provides large-scale empirical support for efforts to quantify a $CO_2$ fertilization effect at smaller scales, and also is able to identify locations where and months when disturbances to the atmospheric concentration of carbon dioxide generate changes in NDVI. The atmospheric concentration of carbon dioxide measured at monitoring station Mauna Loa and Point Barrow. Authors used Granger causality to study the relationship between atmospheric $CO_2$ and terrestrial biota in a way that goes beyond simple statistical correlations.

Results show that NDVI Granger causes carbon dioxide from two or more spatial scales indicating that Eurasian NDVI Granger causes $CO_2$ measured at Point Barrow during May, June, August, and September. Similarly, Eurasian values of NDVI Granger cause $CO_2$ measured at Mauna Loa in May, June, August, September, and October. In North America, NDVI Granger causes $CO_2$ measured at Point Barrow during July only. At Mauna Loa, there is a causal relationship from North American NDVI to $CO_2$ during May and October (Kaufmann et al., 2008).

Some of these causal relationships appear to be concentrated in land covers. In North America, a disproportionate percentage of the grid cells that have a causal effect on $CO_2$ measurements at Mauna Loa in May are classified as mixed forests or croplands. In October, a disproportionate percentage of the grid cells in North America that have a causal effect on atmospheric concentrations of carbon dioxide at Mauna Loa are classified as mixed forests or evergreen needleleaf forests. Similarly, evergreen needleleaf forests account for a disproportionate percentage of North American grid cells that show a causal effect on atmospheric measurements of carbon dioxide at Point Barrow during July. A disproportionate percentage of the Eurasian grid cells where NDVI Granger causes atmospheric carbon dioxide at Point Barrow are located in evergreen needleleaf forests (June and August) and deciduous needleleaf forests (September). The causal effect of Eurasian NDVI on atmospheric concentrations of carbon dioxide at Mauna Loa in August is concentrated in croplands (Kaufmann et al., 2008).

Based on the percentage of vegetated grid cells that show relationship Carbon dioxide causes NDVI at two or more spatial scales in North America only. At Point Barrow, $CO_2$ Granger causes NDVI in North America during May, June, August, and October. At Mauna Loa, there is a causal relationship from $CO_2$ to North American NDVI during June only. For Eurasia, $CO_2$ Granger causes NDVI at a single scale for some months, but there are no months during which this causal relationship is present at two or more spatial scales. When present, the causal effect of atmospheric carbon dioxide on North American NDVI generally is distributed among land covers in rough proportion to their geographic extent. The sole exception is the causal effect of $CO_2$ measured at Point Barrow for June values of North American NDVI, which is concentrated in Cropland.

The enhanced vegetation index, was developed for minimizing canopy-soil variations and for improving sensitivity over dense vegetation conditions. The two products, NDVI and EVI, effectively characterize the global range of vegetation states and processes:

$$EVI = G\frac{NIR - RED}{NIR + C_1 \cdot RED - C_2 \cdot Blue + L} \quad (7)$$

where,

$NIR, RED, Blue$ —atmospherically-corrected or partially atmosphere corrected surface reflectances;

$L$ —the canopy background adjustment that addresses non-linear, differential NIR and red radiant transfer through a canopy;

$C_1, .C_2$ —the coefficients of the aerosol resistance term, which uses the blue band to correct for aerosol influences in the red band;

$G$ —gain factor.

Whereas the Normalized Difference Vegetation Index is chlorophyll sensitive, the EVI is more responsive to canopy structural variations, including leaf area index, canopy type, plant physiognomy, and canopy architecture. The two VIs complement each other in global vegetation studies and improve upon the detection of vegetation changes and extraction of canopy biophysical parameters.

### 3.2 Relation between GPP and PsnNet

Gross Primary Productivity (GPP) product is a cumulative composite of GPP values based on the radiation use efficiency concept that may be used as inputs to data models for calculating terrestrial energy, carbon, water cycle processes, and biogeochemistry of vegetation (MODIS Gross).

GPP describes the total light energy that has been converted to plant biomass. Some of the energy is lost during plant respiration and this fraction can be derived from GPP. The MODIS product which describes the relationship between GPP and the fraction of energy lost during plant respiration is called net primary productivity (NPP). Yet another MODIS product calculates net photosynthesis (PsnNet) by subtracting leaf maintenance respiration and fine root mass maintenance respiration from GPP (Running et al., 1988), while green leaf area index (LAI)—along with FPAR—represents differences in leaf nitrogen content (Heinsch et al., 2003).

Also, MODIS has a product which calculates net photosynthesis (PsnNet) by subtracting leaf maintenance respiration and fine root mass maintenance respiration from GPP.

PSNnet (kg C day-1) can be calculated from GPP and maintenance respiration as (MODIS User's Gide)

$$PsnNet = GPP - Leaf\_MR - Froot\_MR \quad (8)$$

where,

GPP-value of gross primary production;
$Leaf\_MR$ -- maintenance respiration per unit leaf;

$Froot\_MR$ -- maintenance respiration per unit root.

PsnNet are main components for calculating an annual net primary productivity (NPP, kg C day$^{-1}$).

PSNnet for 1km (one pixel) is equal to GPP 1km (one pixel) minus the maintenance respiration from leaves and fine roots. In other words, GPP for 1km should always be ≥ PSNnet for 1km at any given pixel.

## 4. Results and discussion

Using equations (1) – (5) we estimate the level of photosynthesis activity in each time period. The results are graphically presented in Figure 4.

The results indicate that during all spring months the level of biomass influences the $CO_2$ concentration. In summer months the dependence is not so clear. Here we need additional data and more detailed analyses. The results for autumn months are similar to those for spring: the biomass has an effect on $CO_2$ concentration.

In Figures 1 - 4 green lines show the level of $CO_2$ concentration in 2009, red lines show the same value for 2010. Plain line presents the results for forest ecosystem type and dotted - for crop type. Dots reflect the state of photosynthesis in 2009 and squares - in 2010. The relation between carbon flow and carbon dioxide in the atmosphere is described by $h(CO_2)$, between carbon flow and temperature $g(T)$ , and carbon flow and time - $x(t)$. The estimate of photosynthesis level is derived according to $f(h,g,q,x)$.

The results in Figure 1 show that the level of photosynthesis is higher when $CO_2$ concentration is higher. In spring, photosynthesis and $CO_2$ concentration are, in general, higher then in other seasons. At the end of summer and in autumn the $CO_2$ concentration is lower and the photosynthesis activity is poorer, especialy for crop land. It is because plants from previous time periods absorb and will continue absorbing $CO_2$. For crop land, the photosynthesis activity is lower with lower vegetation activity.

Figure 2 displays the dependence of photosynthesis from temperature, eq. (3), when other factors are not limiting. Photosynthesis activity is higher at the beginning of the vegetation period for both types of land cover, but forest type shows higher photosynthesis. In summer when temperature was high and not good for photosynthesis, the level of photosynthesis activity was lower than 1, which shows that condition *(T)* was a limiting factor.

Figure 3 projects the level of photosynthesis activity in different time periods *(t)* when other factors are not limiting. In all points, the levels are higher than 0.7, which means positive photosynthesis state of the plants.

Values derived according to (1) using data on atmospheric CO2 concentration, temperature, time and precipitation in 2009, 2010 years are shown in Figure 4. We see that in general the situation is different for every time period.

The photosynthesis in spring months is higher. In summer photosynthesis activity is lower in 2010. This is because, as seen from Figure 2, temperature was the limiting factor. At the end of the vegetation season in 2009 photosynthesis was higher than in 2010. The results for August 31 and September 8 show that photosynthesis is high but $CO_2$ concentration is lower than in the previous time period when concentration was higher than 372ppm. These points perfectly show interactions between accumulated $CO_2$ by plants and an increase of photosynthesis activity.

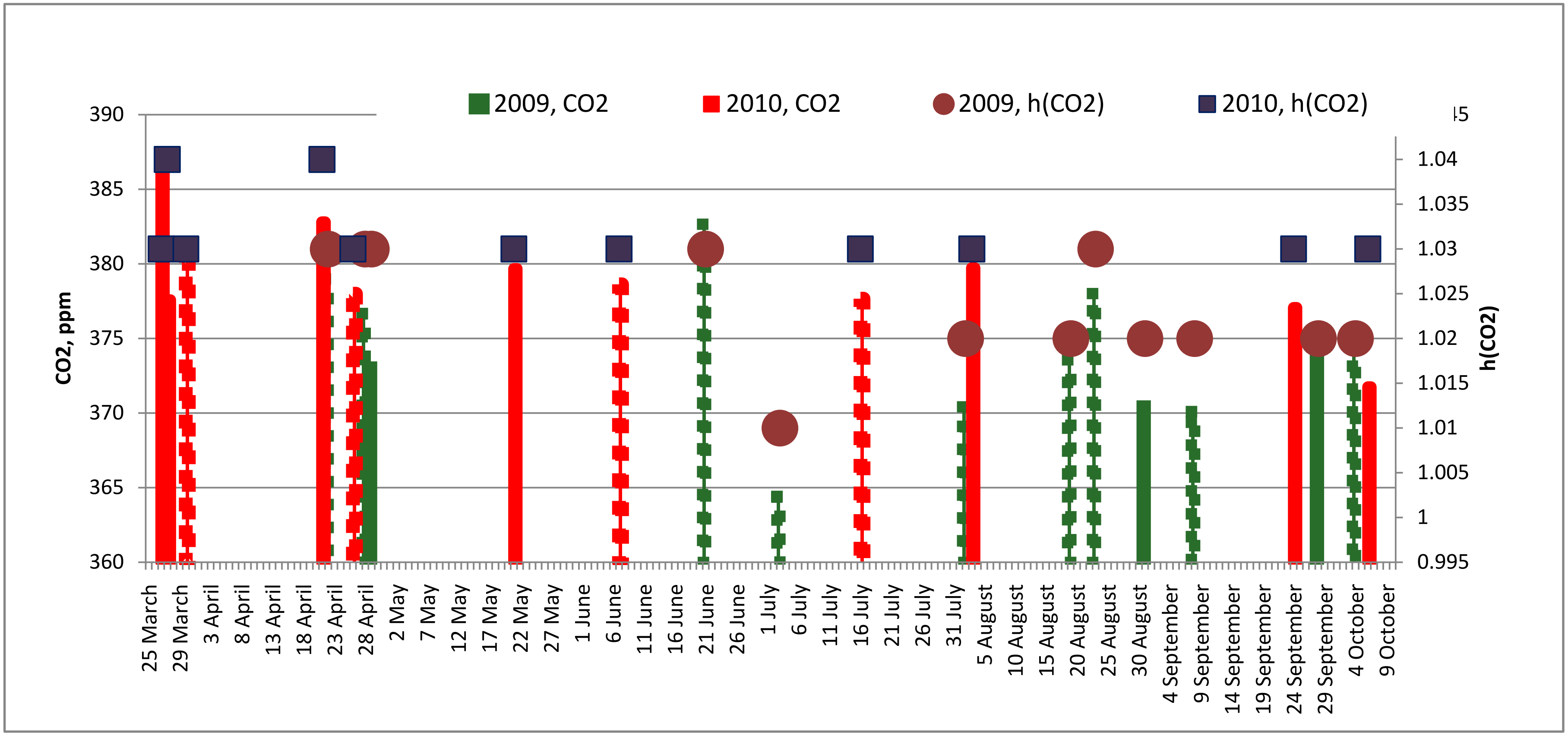


Figure 1. Dependence photosynthesis activity ( *h(*$CO_2$*) )* from concentrated carbon dioxide in the atmosphere in different years (green—2009, red—2010), for different land cover types (plain line — < forest, dotted line — < crop ecosystems)

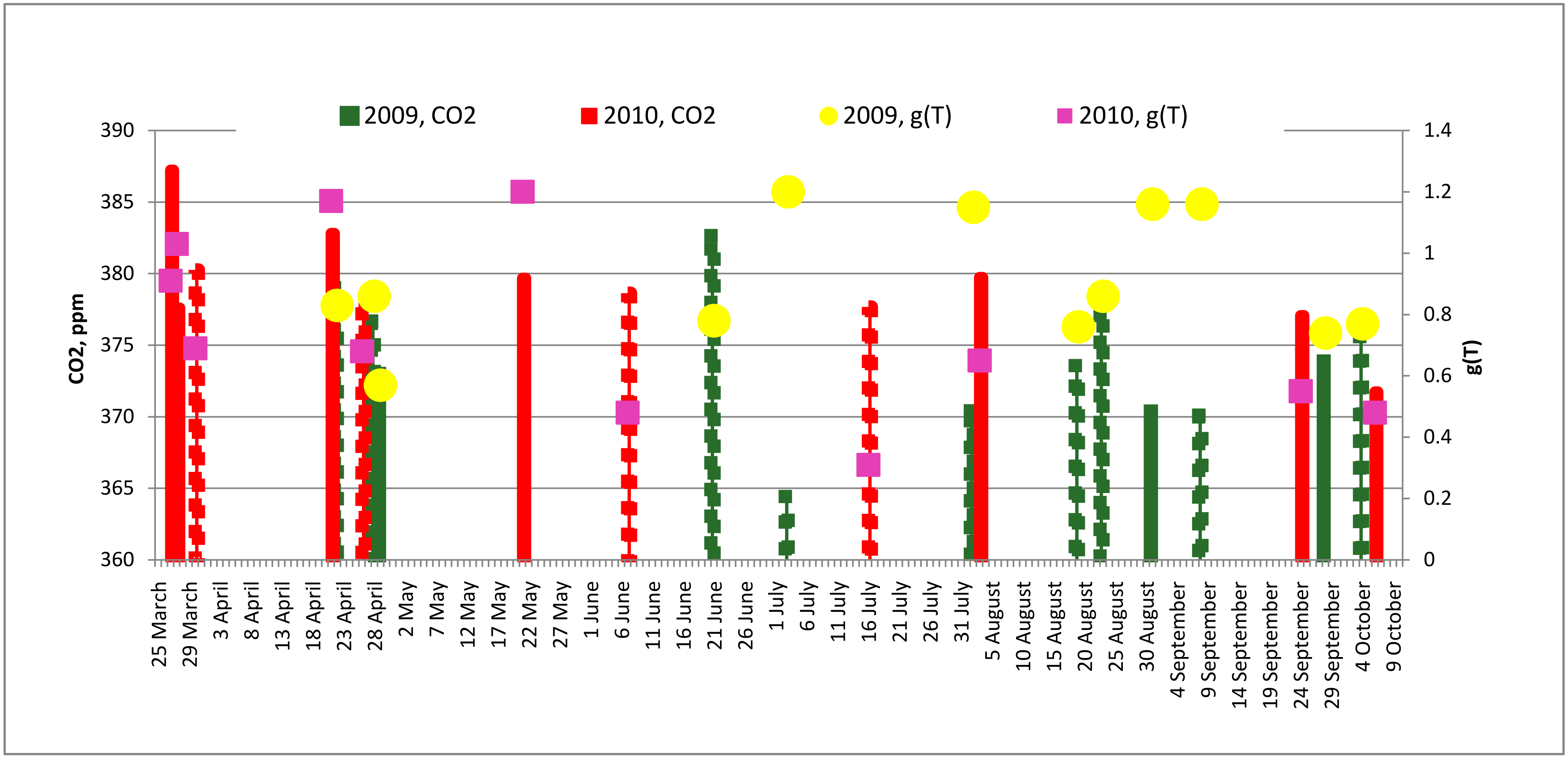


Figure 2. Dependence photosynthesis activity ( *g(T)* ) from temperature in different years (green—2009, red—2010), for different land cover types (plain line — < forest, dotted line— < crop ecosystems)

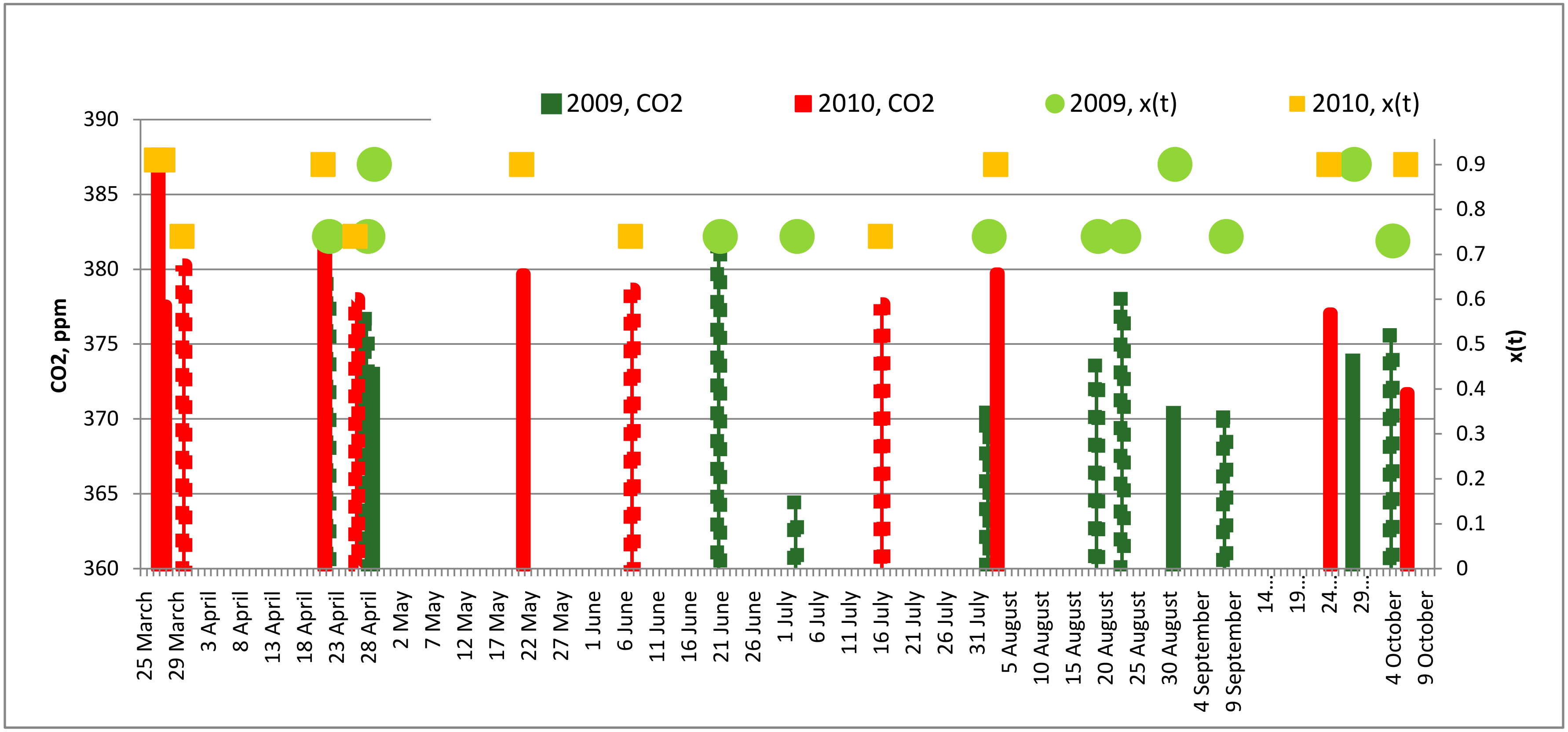


Figure 3. Dependence photosynthesis activity ( *x(t)* ) from period of time (green—2009, red—2010), for different land cover types (plain line — < forest, dotted line— < crop ecosystems)

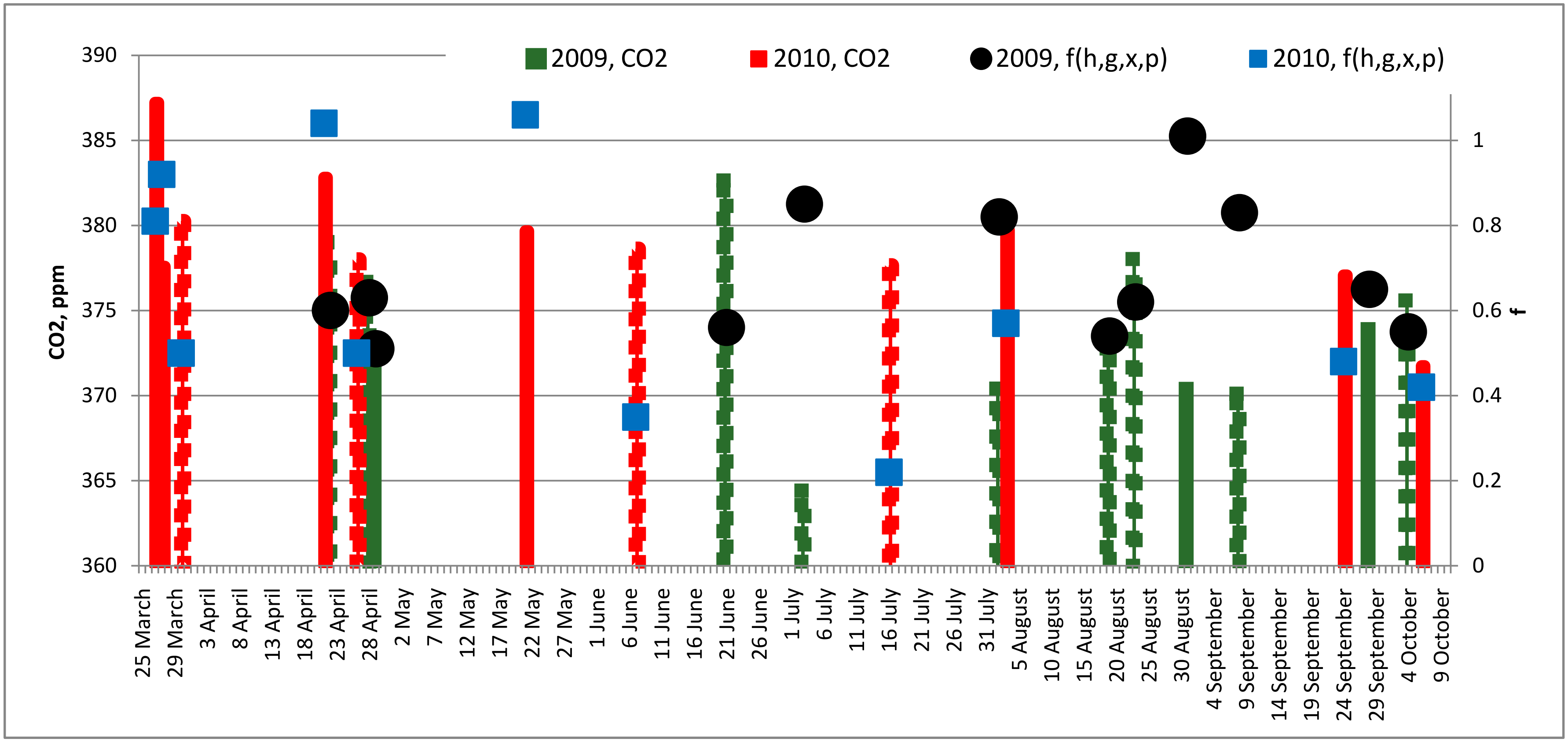


Figure 4. Dependence photosynthesis activity (f*)* which depend from concentrated carbon dioxide in the atmosphere, temperature, time and precipitation in different years (green—2009, red—2010), for different land cover types (plain line —< forest, dotted line— < crop ecosystems)

The next step of this study, correlation coefficients between rate of $CO_2$ and normalized different vegetation index, enhanced vegetation index, Net Photosynthesis and Gross Primary Production and photosynthesis activity were calculated.

Pearson product-moment coefficient of correlation was used to estimate correlation coefficients for every month, season, year with land cover classification and without. Nonzero correlation coefficients indicate the existence of dependencies. In some cases $CO_2$ has positive effects on biomass production (positive correlation coefficient), in other cases—biomass effects the $CO_2$ concentration in the atmosphere (negative correlation coefficient). Tables 2-5 show the values of the Pearson correlation coefficient.

Table 2 shows correlation coefficients between atmospheric $CO_2$ concentration and NDVI, EVI, GPP, PsnNet which were calculated for all points from 2009 and 2010. Table 3 presents the coefficients for all points in 2009 and 2010 together. The values are low because the data used changed with time. For calculation of correlation, correct time resolution is at monthly level, as shown in Table 5.

**Table 2.** Pearson correlation coefficients between atmospheric $CO_2$ concentration and NDVI, EVI, GPP, PsnNet in different years

| | NDVI | EVI | GPP | PsnNet |
|---|---|---|---|---|
| 2009 | -0.03 | -0.04 | -0.14 | -0.29 |
| 2010 | -0.42 | -0.26 | -0.04 | -0.04 |

**Table 3.** Pearson correlation coefficients between atmospheric $CO_2$ concentration and NDVI, EVI, GPP, PsnNet over the two years

| | NDVI | EVI | GPP | PsnNet |
|---|---|---|---|---|
| 2009, 2010 | -0.16 | -0.24 | -0.06 | 0.01 |

Table 4 presents estimated correlation coefficients for two types of points classified by type of land cover: land cover with dominating crop plants (< cropland) which include points in 2009 and 2010 an land cover with dominating forest (< forest) in 2009 and 2010. In 2009 and 2010 the coefficients are higher for forest land cover type than for cropland type. This is because cropland biomass changes during vegetation period are very irregular. At the beginning of the period biomass increases rather fast. In the middle - biomass as usual does not change considerably, and at the end—biomass decreases. The rates of these changes are different for different types of agricultural cultures. This study does not distinguish crop land by crop types. A more detailed classification of cropland would help to specify plant and choose the indexes more exactly $\varphi_{ph}, \beta, Z, T_{opt}$ in the 1,2,3,5.

**Table 4.** Pearson correlation coefficients between atmospheric $CO_2$ concentration and NDVI, EVI, GPP, PsnNet in different years for different types of the land cover type

| | NDVI | EVI | GPP | PsnNet |
|---|---|---|---|---|
| < cropland, 2009 | -0.07 | -0.03 | -0.09 | -0.3 |
| < cropland, 2010 | -0.68 | -0.55 | -0.47 | -0.19 |
| < forest, 2009 | -0.77 | -0.18 | -0.93 | -0.71 |
| < forest, 2010 | -0.47 | -0.26 | -0.05 | -0.07 |

Forest biomass changes are more stable during March-October. Without output factors, the biomass grows with a rate specific for the type of forest. Foliage forests have similar growth characteristics as croplands: at the beginning biomass grows faster, in the middle biomass does not considerably change and at the end biomass decreases. Conifer forests normally increase their biomass during the course of a year (except for winter, when biomass stops to grow). But if the conditions are limiting factors or on this territory provided cut occupation biomass will decrease. These results can be explained by the fact that temperature in 2010 was “stressful” and the loss of biomass was due to defoliations. This may be the reason for lower correlation coefficients in 2010 than in 2009 when temperature was not a stressful factor. Forests data was also not classified by forest type e.g. conifers or foliage forest. A more detailed classification and analysis of condition would provide more precise estimates of coefficient.

In Table 5 the higher correlation coefficient between atmospheric $CO_2$ concentration and indexes are observed for September for indexes NDVI and EVI. For NDVI the coefficient is positive, for EVI it is negative. In the first case it indicates that $CO_2$ influences the biomass growth, in the second that biomass affects $CO_2$ concentration. Strong dependencies are observed in March, both correlation coefficients are negative.

**Table 5.** Pearson correlation coefficients between atmospheric $CO_2$ concentration and NDVI, EVI, GPP, PsnNet in different months over different years

| | NDVI | EVI | GPP | PsnNet |
|---|---|---|---|---|
| Spring mounts | -0.49 | -0.65 | -0.15 | -0.15 |
| March | -0.80 | -0.92 | -0.85 | -0.84 |
| April | -0.3 | -0.53 | 0.62 | 0.5 |
| May | insufficient data | | | |
| Summer mounts | 0.06 | 0.08 | -0.15 | -0.42 |
| June | insufficient data | | | |
| July | insufficient data | | | |
| August | 0.31 | 0.47 | -0.55 | -0.87 |
| Autumn mounts | 0.42 | -0.22 | -0.46 | -0.26 |
| September | 0.99 | -0.9 | -0.17 | 0.32 |
| October | insufficient data | | | |

Figure 5 displays Pearson-moment coefficients of correlation graphically, both for NDVI and EVI. Figure 6 displays Pearson-moment coefficients of correlation shown for NDVI, EVI, GPP and PsnNet.

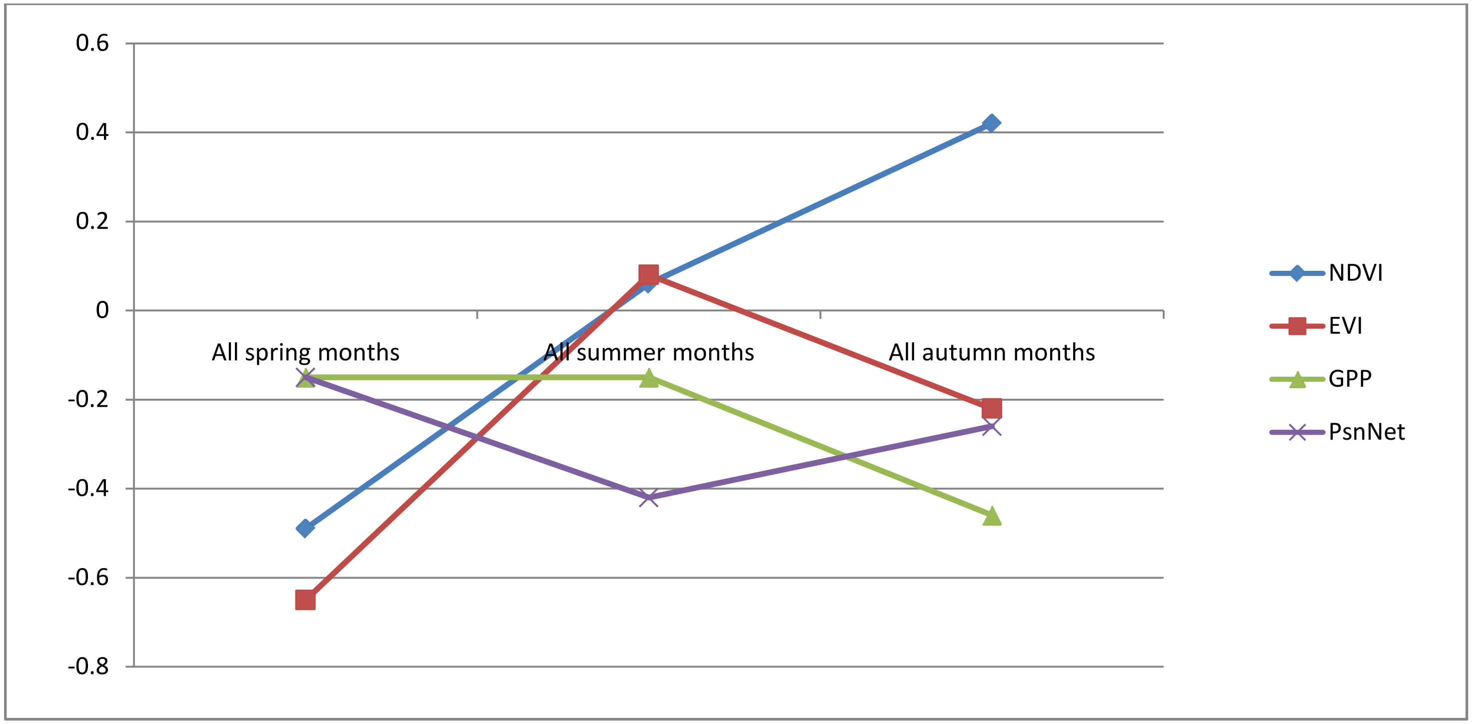


Figure 5. Pearson product-moment coefficient of correlation between indexes and $CO_2$ atmospheric concentrations in seasons

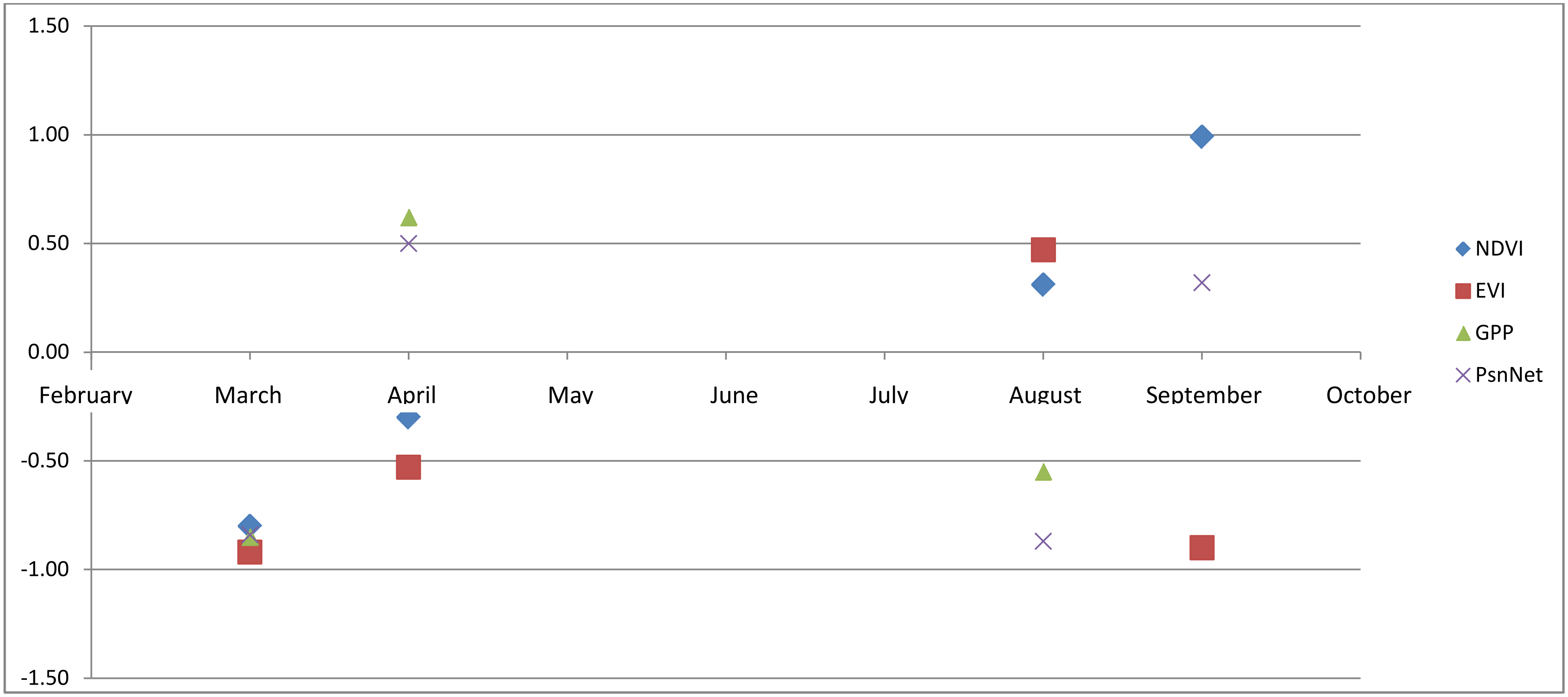


Figure 6. Pearson product-moment coefficient of correlation between indexes and $CO_2$ atmospheric concentrations in months

## 5. Conclusions and further work

The results of this project estimate the correlation between $CO_2$ atmospheric concentration and environmental indexes derived from remote sensing data. Some correlation coefficients are very low (0.01) and others are satisfactory (0.99; -0.93). The satisfactory correlation was statutory authority between EVI and $CO_2$ (March, September), NDVI and $CO_2$ (September), GPP and $CO_2$ (forest land cover, 2009). It means that in this period it is more reliable to make a hypothesis about an increase or decrease of $CO_2$ concentration in the atmosphere. It was analyzed that plants at the beginning of the vegetation season (start of spring) have a more significant effect on $CO_2$ concentration.

The estimates of coefficients for summer months do not have a clear explanation because data were not sufficient. More information and research points for the analyses of the dependencies between $CO_2$ concentration and biomass increase would improve conclusions. In general, the results of the research indicate a promising direction of using spectral indexes for the analyses of dependencies between $CO_2$ concentration and biomass state.

Future work includes the analysis of all 24 regions of Ukraine, with a focus on three naturally-climatic zones: Wood, Steppe, and Wood-Steppe regions. Analysis will be conducted for more types of land cover classes, in particular, with the possibility of taking in account forest types.

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