The Use of Remote Sensing and Automated Water Quality Systems to Estimate Greenhouse Gas Emissions from Hydroelectric Reservoirs

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1 - Introduction

Aquatic environment science has arrived at a stage where many of the significant problems which could be tackled with point sampling from boats have been taken as far as is practical with presently available technology. Moreover in recent years, it has become clear that many water quality problems are influenced by short-term changes in the forcing functions as well as long-term changes in the drainage basin. The understanding of different time and space scales of environmental processes require sequenced and synoptic data, which can only be provided by the integration of remote sensing technology into the current methods. This understanding is crucial for addressing the main issues of the 21st century environmental agenda, which focus on global change and sustainable development.
Since the United Nations Conference on the Human Environment held in Stockholm in 1972 there is a steady increase in the worldwide awareness that the carrying capacity of the Earth’s resources is limited. The focus of environmental monitoring and assessment programs has changed so as to provide reliable information in support to national, regional and global policy formulation, action planning and implementation management (Vandeweerd, 1997). As a consequence, the identification and monitoring of indicators of the State of the Environment (SoE) became a key scientific issue (Fedra, 1997). There is a growing need of new methods for assuring that the global indicators are measured with precision over different time and space scales. At present, however, the precision to which those indicators have been measured varies drastically from country to country and from indicator to indicator. Some are measured with well-defined straightforward methods, whereas for others the methods are yet to be fully developed.

Among the indicators, the assessment of anthropogenic emissions of Greenhouse Gases (GHG) is one of the most controversial. First, there are many natural sources and sinks of GHG whose baselines are barely known. On top of that there are many factors affecting both natural and anthropogenic emissions and their future atmospheric concentrations such as world population growth, socio-economic development, technological advancement. In addition to that, regional and global estimates of GHG emission vary considerably and have large uncertainties related to both, limited measurement of fluxes and lack of reliable ways of extrapolating point measurements. According to Melack and Hess (1998) recent advances in remote sensing offer the basis to reduce that uncertainty. On the other hand, systems for real time acquisition of satellite and in situ water quality and environmental data offer unique insights on the dynamic interactions among environmental variables at different time scales. Satellite tracked moored and drifting platforms are being used to collect real time in situ data to both validate satellite data and unfold environmental process at very fine time scale.

The purpose of this article is hence assessing the use of new technologies as a tool for improving the extrapolation of GHG emissions from aquatic environments. First, the paper will provide a broad overview or remote sensing applications for reservoir management. Then it will focus on remote sensing applications to improve the extrapolation of methane emission rates from hydroelectric reservoirs. Finally, an Automated Water Quality Monitoring System (SIMA) developed through a partnership between the National Institute for Space Research and the University of Vale do Paraíba in Brazil, will be presented as well as the ongoing research based on data provided by the system (Stevenson et al., 1993; Novo et al., 2002).
The earliest attempts to apply remote sensing for reservoir management were accomplished in the 70's when data from the Multi-Spectral Scanner (MMS) carried on Landsat-1 was used to map seasonal changes in water surface area. At that time, simple threshold technique on the infrared band allowed to distinguish between bodies of water and their surroundings and then to estimate the area of each reservoir. Those studies showed that remotely sensed data, obtained from satellites could provide estimates of water surface area within acceptable accuracy. The combination of multiple date images allowed to monitoring reservoir capacity as well as to have a continuous survey of new and existing dams.

Since then, a larger number of satellites carrying new sensor with improved spatial, spectral and radiometric resolution became available and the range of potential applications increased dramatically. Distribution pattern of high-reflectance patches of algal blooms has been mapped using multispectral classification algorithms (Brown and Yorder, 1994); some water constituent concentration were also estimated directly by remote sensing techniques, such as phytoplankton pigments, suspended particulate matter and gelvin (Dekker, 1993). Novo et al. (1993) report the results of a four-year research project carried out to assess the feasibility of using TM/Landsat data to monitor the water quality in eutrophic tropical reservoirs. Eighteen in situ water quality data collection missions were performed concurrently to Landsat overpasses from May 1989 to October 1991. During this period six cloud-free Landsat scenes were acquired. The authors concluded that although TM/Landsat data were not specially designed for water studies, they could give useful and consistent information about inorganic matter concentration and about the optical conditions of the aquatic medium.

Specific pollution sources as hydrocarbons patches can also be monitored using active microwave sensors. Oil slicks on the water surface tend to dampen the radar backscattering coefficient. As a result, the slick presents a darker tone than the unpolluted area. The detection rates, however, varies with the observation conditions, since the water surface state also affects radar backscattering. At high winds, it is not possible to discriminate biogenic slicks from oil. At low wind speeds, however, it was found that images in the L-band showed discrimination. Radar has also been used to measure currents and predict oil spill movements by observing frontal movements. For equal wind conditions, therefore, radar backscatter can be used to oil slick pollution (Fingas and Brown, 2000).
Radar orbital images have been also applied to distinguish between floating macrophyte genus. (Novo et al., 1998; Costa et al., 1998; Noernberg et al., 1999; Costa, 2000, Novo et al., 2002, Costa et al., 2002). At present, the results suggest that the combination of L and C bands are essential to distinguish between those species with and without flat planar leaves. The backscatter is also sensitive to stand height (Novo et al., 1998) and biomass (Costa, 2000). A SAR based methodology was also developed for quantifying the annual net primary productivity (NPP) of aquatic vegetation (Costa et al., 2002). The combination of seasonal maps of aquatic vegetation derived from multi date radar images and radar derived biomass estimates allowed to calculate seasonal changes in total biomass. Radar backscattering was also found to be sensitive to the proportion of green to senescent leaves and stems, and effects of senescence on stem and leaf orientation (Hess et al. 2003).

The integration of optical and radar data, however, increases the discrimination between species (Graciani and Novo, 2002). Macrophyte leaf shape and height are distinguished through differences in backscattering whereas changes in leaf water content and leaf photosynthetic pigments are better assessed with optical images.

Optical remote sensing methods have been extensively used to monitor aquatic macrophytes in reservoirs. Malthus and George (1997) report the use of optical remote sensing for distinguishing selected species of submersed, floating leaved and emergent macrophytes. The study combined ground-based spectro-radio-metric and airborne imagery; results indicated that differences in reflectance are attributable to growth habits as well as to depth and turbidity of the surrounding water. Remote sensing has also been used to estimate pigment composition and photosynthetic behavior of aquatic emergent plants using narrow band sensors (Pannecas et al., 1997).

Landsat Thematic Mapper (TM) proved to be useful to differentiating genus of aquatic macrophytes in Tucurui reservoir. According to the authors (Abdon and Meyer, 1991) there is striking reflectance differences between Salvinia, Eichhornia and Scirpus stands. TM images were also used to study the relationship between decadal land use changes and macrophyte infestation in Tucurui Reservoir. According to Pereira Filho and Novo (2001) the rate of macrophyte infestation showed to be affected not only by the actual land use. The land use history is also an important factor affecting the spread of macrophyte at a given reservoir inlet.
The availability of hyperspectral sensors such as EO-1 Hyperion opens a new perspective to the use of orbital remote sensing for water quality monitoring. Galvão et al. (2003) used airborne hyperspectral data to distinguish between saline and fresh water lakes in Pantanal. Though, it is important to stress that the operational use of remote sensing for water quality monitoring is still dependent on a better understanding of how the various optical components affect the water reflectance.

More recently remote sensing data are becoming an essential input to run ecological models. Algal growth and respiration rates can be estimated using a one-dimensional water quality model (QUAL2E) and two-dimension spatially distributed water quality data derived from SPOT satellite imagery for the Te-Chi Reservoir in Taiwan (Yang et al. 1999).

III — Remote sensing and automated water quality systems applications to monitor greenhouse gas emissions from reservoirs.

Spatial and seasonal aspects

Assuming functional similarities between reservoirs and natural lakes Novo and Tundisi (1994) proposed the use of Landsat Thematic Mapper images to improve the estimates of methane fluxes. Color composite of Landsat TM bands 3, 4 and 5 at the scale of 1:250 000 were used to distinguish four different habitats: open water, dead tree/macrophytes, marginal dead trees/degraded forest (areas which are only flooded during two or three months in a year), seasonally flooded marginal areas. Methane emissions available from the literature (Bartlett et al., 1988) were combined with habitat area and distribution to derive methane estimates for the three largest reservoirs built in the Amazon region: Tucurui, located in South Para State, Balbina, located near Manaus, Amazonia State and Samuel, located in Rondonia, near Porto Velho. In spite of the flaws and uncertainties derived from the lack of “in situ” data for each reservoir habitat, the authors concluded, at that time, that methane flux from those reservoirs was negligible when compared to that of natural sources. They also highlighted the importance of remote sensing data as a source of spatial information.

Multi date TM images were applied to study the role of the spatial and inter-annual variability of floating macrophytes on methane emission from Tucurui reservoir (Lima, 1998). Five dates were selected: June/86, August/88, July/90, June/92, and July/94. To improve the digital classification, a mask over the reservoir was created and multiplied by each image, selecting only macrophyte and water/dead tree targets. Bands 3, 4 and 5 were used in the unsupervised classification for each date (Figure 1).
Figure 1 - Space time map of the evolution of macrophytes in Tucurui reservoir. Accordingly to Lima et al. (1998), green areas represent areas covered only in 1986, whereas red denotes places permanently occupied. In blue areas no macrophytes were found in any year and yellow sites represents sporadically covered sites.

From August 3 to 14 in 1997 a ground sampling was carried out at Tucurui reservoir. Classified images were used to define sample stations, which were divided into two major groups: tributaries often covered by floating macrophytes and the main channel. Table 1 shows the results for the two environments.

Table 1. Methane fluxes in the Tucurui reservoir from August 3 to 14, 1997.

<table>
<thead>
<tr>
<th>CH₄ fluxes (mgCH₄ m⁻² d⁻¹)</th>
<th>Tributaries</th>
<th>Main channel</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average</td>
<td>86.48</td>
<td>33.00</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>59.97</td>
<td>15.88</td>
</tr>
<tr>
<td>Maximum</td>
<td>248.63</td>
<td>66.75</td>
</tr>
<tr>
<td>Minimum</td>
<td>14.76</td>
<td>20.53</td>
</tr>
<tr>
<td>n</td>
<td>25</td>
<td>7</td>
</tr>
</tbody>
</table>

Source: Lima et al. (1998)
Despite the small number of samples for the main channel, the nonparametric test Wilcoxon-Mann-Whitney determined significant difference ($p < 0.05$) between these environments related to the sediment anoxia in tributaries often covered by macrophytes. As shown in Table 1 methane fluxes in the tributaries are much higher than in the main channel. This can be related among other factors to the fact that macrophyte stands might be an additional source of C.

The large amplitude in methane flux in the tributaries ($233.87 \text{ mg CH}_4 \text{ m}^{-2} \text{ d}^{-1}$) can be attributable to the large variability in macrophyte species composition in the area. This variability in space and time should be taken into consideration in future studies. Cloud cover prevented the use of optical remote sensing to assess the seasonal variability of macrophyte stands. To overcome this problem a study was carried out to assess the feasibility of using multi-date RADARSAT images to map the area occupied by macrophyte stands in Tucurui reservoir (Ballester et al., 1997).

During May (rising water), August (high water) and November (low water) 1996, water and gas samples for methane concentration determination were collected concurrently with the RADARSAT acquisition for three different environments: open water, macrophyte beds and flooded forest at Tucurui reservoir (Para, Brazil). Image pre-processing for correcting radiometric and geometric distortions were applied. Calibration data provided by RADARSAT allowed the conversion of digital numbers to radar backscatter coefficient. The images were ortho-rectified by integrating the complete viewing geometry, Earth’s characteristics and the cartographic projection. Maps (scale of 1:100 000) were used for the collection of ground control points to complete the registration (Costa et al., 1997). An isocluster (interactive self organizer) classification algorithm produced a three classes map for each date: open water, macrophytes and water/dead trees. Computing the proportion of pixels from each class in relation to the number of pixels belonging to reference polygons determined on the ground assessed classification accuracy. The average user accuracy (Richards 1995) was computed for each date (Table 2). The number of pixels in each class was used to determine the proportion of the reservoir occupied by the different habitats. This proportion was then extrapolated to the entire reservoir.

<table>
<thead>
<tr>
<th>Date</th>
<th>Open Water</th>
<th>Dead Tree Trunk</th>
<th>Macrophyte beds</th>
<th>Overall user accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>May 27, 1996</td>
<td>99.0 %</td>
<td>66 %</td>
<td>59 %</td>
<td>75.3 %</td>
</tr>
<tr>
<td>August 14, 1996</td>
<td>85.8 %</td>
<td>70.3 %</td>
<td>59 %</td>
<td>70.5 %</td>
</tr>
<tr>
<td>December 5, 1996</td>
<td>81.9 %</td>
<td>70 %</td>
<td>51 %</td>
<td>73.9 %</td>
</tr>
<tr>
<td>Average</td>
<td>88.9 %</td>
<td>68.8 %</td>
<td>56.3%</td>
<td>73.3 %</td>
</tr>
</tbody>
</table>

Source: Novo et al. (1998).
As observed in Table 2 although the overall user accuracy is reasonable (~70 %), the class accuracy varied drastically from macrophyte stands (~50 %) to open water (~90 %). The confusion matrix for the data showed a very high mixture between three-trunk and macrophytes. That is expected because on the ground there is no pure macrophyte stands in a reservoir that flooded a standing tropical forest (Figure 2). As pointed out by Novo et al. (2002) frequency of emerging trees varied with the reservoir bottom topography (shallower areas having large number of standing dead trees) making it difficult to separate those classes with single band radar data.

Figure 2 – Macrophyte stands in Tucurui reservoir. In the first plan an Eichhornia stand. In the back a mixture of Scirpus, dead tree trunks. The panel is a device used to measure canopy roughness.

This problem was overcome by clumping the two classes into a single ground class. Figure 3 shows the time changes in the open water and dead-tree/macrophyte classes derived from RADARSAT images.
As shown in Figure 3, the area covered was drastically reduced from May to December as the reservoir water level dropped from 72 meters to 62. The macrophyte community starts to spread during the rising water (May) reaching its maximum during the high water period (June - July). In August, they still cover an area larger than in May, but by December dense dead tree stands and organic detritus replace the macrophytes. This can be observed in Figure 4, which shows the multi-date colour composition of the RADARSAT images.
In Table 3 one can observe the average flux of methane for each reservoir habitat.

Data was collected taking into consideration the functional distinction between the three ground classes: open water, macrophyte stands and dead tree trunks.

**Table 3 — Average methane fluxes (mg.CH₄.m⁻².day⁻¹).**

<table>
<thead>
<tr>
<th>Date</th>
<th>Open Water</th>
<th>Dead Tree Trunk</th>
<th>Macrophyte beds</th>
</tr>
</thead>
<tbody>
<tr>
<td>May 27, 1996</td>
<td>12(3.3)</td>
<td>893.2(77)</td>
<td>73.1(4.8)</td>
</tr>
<tr>
<td>August 14, 1996</td>
<td>32.2(5.1)</td>
<td>85.4(20.2)</td>
<td>63.7(6.6)</td>
</tr>
<tr>
<td>December 5, 1996</td>
<td>64.8(11.8)</td>
<td>960.3(282)</td>
<td>72(5.64)</td>
</tr>
</tbody>
</table>

Dead tree trunk habitats produced the highest methane fluxes in May and December. In August, the fluxes were very low compared to May and December, and they do not differ from one habitat to the other. The high emissions in May and December can be explained by the reservoir operation. From November to April (Figure 5), the water level drops and a large area of the margins is exposed and
occupied by terrestrial vegetation. The runoff input of organic carbon also increases during the rainy season. When the water level rises and the vegetation becomes subjected to anaerobic decomposition a new maximum may take place. In short, higher fluxes in the beginning of the hydrological year is derived from both autochthonous and allochthonous carbon, and in the end of the year derived basically from autochthonous carbon. From May to August, during the dry season no external input of organic matter is added to the system and the macrophyte beds profit from the nutrient released from the decomposition by successive growing cycles undergone by the stands. In August the stands reach their maximum biomass (Mantovani et al. 1997). In September, water level recedes imposing a serious stress on the macrophyte beds, which began to dye and to decompose. The death and decomposition of the macrophyte beds reaches their maximum in November. Between August and December there was a decrease in the area occupied by macrophytes. That area is converted to water/dead trees. During that period anoxic conditions are common. Dissolved oxygen is very low (average saturation \(\sim 1.15\%\)) at the bottom, resulting in the decomposition of the dead macrophyte community under anaerobic conditions and methane production. It is noticeable however that the macrophyte community in Tucurui has been disappearing exponentially since reservoir formation, and probably its significance as a Carbon source is accordingly decreasing. This does not mean that methane production will be lowering along the years, since the absence of acetate is compensated by the utilization of \(\text{H}_2/\text{CO}_2\) as substrate in bacterial methanogenesis. As verified by isotopic analysis, most of the methane bubble confined in the sediments in July 2001 are depleted in \(^{13}\text{C}\), evidencing \(\text{CO}_2\) reduction as a major methanogenic pathway rather than acetate fermentation (Lima, 2002).

Figure 5 — Reservoir level variation in 1996 and in the decade.
Remote sensing and dynamical aspects

The transfer of methane from the sediments to the atmosphere follows generally molecular diffusion, plant stem diffusion and bubble releases. From that, methane fluxes are strongly variable in space. In addition, a reservoir is subjected to several external variables, such as wind speed, temperature, atmospheric and hydrostatic pressure, that increases uncertainties in space and in time. Hence, the process of methane emission in hydroelectric reservoirs is an open system with many degrees of freedom (Lima, 2002). System of this type is usually denoted as a complex system, with several interacting variables. Complex systems are difficult to simulate, due to the high number of coupled non-linear equations necessary for creating a suitable model.

The Heisenberg's principle of uncertainty is fairly applicable in the issue of methane emissions. Concentrating measurement efforts in space, information on flux dynamics in time is reduced, whereas, focusing on one single station for long periods, the information in space variability is lost. Any strategy of methane fluxes should therefore consider a compromise of covering together spatial and temporal resolutions. However, reservoirs are often large systems, and a suitable strategy as delineated above is in general costly prohibitive.

In order to achieve a desirable minimal level of uncertainty in methane flux measurements, it is reasonable to focus the efforts in an attempt to elucidate dynamical rules between the dependent variable (methane fluxes) and factors causing its changes. For instance, methanogenesis rate in the sediments is directly related to temperature changes (Dalauto & Clymo, 1998; Macdonald et al., 1998). Depending upon substrate availability and the presence of competing bacteria, methane formed in the sediments can be rich or depleted in $^{13}$C, influencing bacterial oxidation in the water column, and thus the amount of methane emitted to the atmosphere (Lima, 2002). The sum of hydrostatic, atmospheric and Laplacian pressures give the total pressure of methane bubbles in the sediment. For that reason, atmospheric pressure in shallow sites and reservoirs (lower hydrostatic pressure) and Laplacian pressure, regarding bubble shape and sediment texture and densities, can modulate the frequency of methane bubble releases (Lima e Novo, 1999; Lima, 2002).

Due to the complex nature and cost demands for confidently estimate methane fluxes, remote sensing techniques seems to be a suitable approach. Firstly, remote-sensing images is becoming quite accessible and costly effective for environmental studies. As a result, the use of remote sensing techniques such as the one described in Novo and Tundisi (1994), Lima et al. (1998) and Novo et al. (2002) is quite
appropriate for evaluating spatial aspects of methane flux variability in reservoirs. Another important question is the hypsographic curve, which can be used for investigating seasonal variation of a given reservoir area, allowing evaluation of the annual methane flux pulsation. In association to the spatial covering, remote sensing platforms can collect routinely information on the variability of variables recognized as important factors in the modulation of methane fluxes, such as the water level, gradient temperature of the water column, wind speed and atmospheric pressure.

In situ measurements of methane fluxes near the platform can be used for the establishment of the dynamical rules cited above, and used in space-time proxy models, suitably designed and parameterised for a given system, according to the obtained empirical data. For instance, Lima (2002) have used a long time series of the water depth in the Tucuruí reservoir as a proxy for estimating methane fluxes by the utilization of two dynamical rules \( A \sim c \cdot h^a \), and \( F \sim c \cdot h^{a_f} \), where \( A \) denotes the reservoir area, \( F \) the average methane flux, \( h \) the water depth, \( c \) a constant defining the range of the variable, and finally an exponent \( a \) determining the type, magnitude and intensity of the dynamical relation. By this approach a close-real dynamics could be modelled and the total methane emission evaluated for the entire reservoir lifetime.

IV – Automated environmental data collection

Since the early eighties (Stevenson et al., 1993; Friey et al., 1999) there has been a steady use of technology to remotely sense environmental variables. The ability to retrieve large amounts of data within hours of its being collected coupled with the ability to send commands to the data platform has changed the way remote experiments are carried out by the oceanography community (Shaumeyer et al., 1999). Most of those systems have already been in operation in ocean monitoring for at least a decade (Vianna et al., 1999). The PIRATA Program (Pilot Research Moored Array in the Tropical Atlantic) was designed to install and maintain an ocean observing system in the tropical Atlantic based on an array of 12 moored stations with satellite transmitting capability. The main objective of this system was to monitor atmospheric-oceanic surface variables and upper ocean thermal structure at optimal locations in the Tropical Atlantic. High-resolution data from the stations are made available through Internet, and is being extensively used in research projects (Castelão, 2002).

The first attempts of using automated data collection in freshwater systems was carried out using microcomputer-based control to monitor environmental conditions in aquaculture research and industry activities. The systems were designed for
several research groups interested in modelling aquatic environment processes. The systems differed in actual variables measured and controlled but most of them were able to obtain at least the following: dissolved oxygen, water temperature, pH, solar irradiance, relative humidity, rainfall, wind speed and direction (Lee, 1995).

Automated systems are also being proposed for water quality monitoring in river basins subjected to concurrently wastewater discharge and drinking water supply. Identification of water pollutants (and polluters) was often impossible because water samples could not be secured for analysis in time. According to Bode and Nush (1999) experience and results showed that automated water quality monitoring systems permit accidental water pollution warning and treatment, and is being proposed for the Ruhr basin.

An integrated continuous water quality monitoring system was also designed and implemented as part of the Land-Ocean Interaction Study (LOIS) Rivers Program (Evans et al., 1997). The objective of the program is to characterize intermittent flood events that are most significant to the transport of sediments and chemical species into the coastal zone via rivers. The system consisted of a combination of a pressure transducer for stage measurement, two turbidity sensors and automatic samplers and data logger and telemetry facility to enable remote interrogation.

Following the science and technology trend of the 90’s Stevenson et al (1993) designed an Integrated Environmental Monitoring System (SIMA) for monitoring aquatic environment. The system implemented in the following years through cooperation between the National Institute for Space Research and the University of Vale do Paraíba and consisted of a) an instrumented buoy with digital electronics for the collection and transmission of data and environmental sensors installed above and below the water surface; b) a VHF radio receiver for satellite data connected to a PC microcomputer; and c) a set of specially developed programs for processing and analyzing the data received. Typical variables monitored by the system are: wind direction and speed, air temperature, relative humidity, solar radiation incident and reflected, atmospheric pressure, water temperature, current direction and speed, water turbidity, water level, water pH, dissolved oxygen, and chlorophyll.

The subsystem for data collection consists of an instrumented toroidal buoy (Figure 6) weighting around 750 kg and having 2.3 m in diameter. The environmental data are transmitted to either of the two NOAA and Brazilian satellites (CBERS and SCID) satellites passing over the buoy, using a Data Collection Platform (DCP). A microprocessor linked to an electronic circuitry allows the sensor to be sampled at hourly intervals; it also permits the data to be stored in successive bins in the memory and then be transmitted in sequence during the normal operation of the SIMA.
The prototype of the system was anchored in the Paraibuna Reservoir, São Paulo state during several months as proof of concept and then transferred to a private company which was responsible for building an operational version of the system which was acquired by the Brazilian Navy. This system was deployed in the shoreline of Rio de Janeiro State, and gathered information of air/water temperature, wind speed, and atmospheric pressure, along approximately two years. The data was transmitted by the NOAA satellite, and the association of the Brazilian Navy and the Global Oceans Observing System (GOOS) make the data available to the research community. Figure 7 exemplifies the sort of high frequency time series for four levels temperature obtained by the system.
Figure 7 – Temperature time series acquired by SIMA.

At present Steeh et al. (2002) and Novo et al. (2002) are carrying on research projects, which will rely on data collected with the SIMA. The Furnas project, a research cooperation among COPPE, IEE, UFJF and INPE was conceived to provide a better understanding and estimations of greenhouse gas emissions from hydroelectric reservoirs spread around the Brazilian Savannah, commonly known as Cerrado. INPE's participation includes data acquisition in the water-air interface with SIMA platforms associated to in situ measurements of concentrations, isotopes and fluxes of greenhouse gases. It is expected that by gathering both SIMA and in situ data it will be possible to define dynamical rules between variables, and build up proxy dynamical models using alternative variables for estimating greenhouse gas emissions from reservoirs, as proposed in Lima (2002). In addition, time series will be evaluated in non-linear analysis for statistical physics studies, modelling and applications.

The SIMA-CTHIDRO project is studying two aquatic ecosystems undergoing different degrees of human interference. The Tucurui Reservoir feeds a hydroelectric power plant, and the Lago Grande de Carnai, is a large Amazon floodplain lake in relatively pristine conditions. The specific objectives are to install an automatic monitoring system for the limnological variables that could support a more comprehensive assessment of the role of the hydroelectric reservoir as source of green-
House gases. A first exploratory mission was carried out in Lago Grande de Curuai, Pará State, in July 2002 in order to identify suitable sites to anchor the buoy. Figure 8 shows colour changes displayed by a Landsat TM composite. As these water colours are related to Amazon river water input to the lake, changes in high frequency water quality and other environmental variables measured by the SIAM coupled with satellite data can be used to better understand the connections between greenhouse gas emissions from floodplain lakes and river stage fluctuation.

Figure 8 – Landsat Thematic Mapper Colour Composite 2(B), 3(G), 4(R), (TM). Date: 09/06/1992

V – Conclusions and recommendations

In summary, the association of remote sensing and dynamical rules is an excellent alternative for estimating greenhouse gas emissions in hydroelectrical reservoirs and natural wetlands, since they together provide reliable information for process modelling, and also establish a rational compromise of decreasing space-time-uncertainties and costs.
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