Copernicus Tools for Monitoring Global Change Effects in Rivers and Riparian Zones

(Cop.RIVER)

Deliverable 2: Selected terrestrial and aquatic remotely sensed indicators

INDEX

1 BACKGROUND

Cop.RIVER aims to promote the use of Earth Observation (EO) in applications and services related to the ecological status of riverscapes (i.e. rivers and their associated alluvial plains, floodplains and riparian forests). The action will strengthen the Copernicus user uptake by supporting regional and national authorities in the implementation of the EU Biodiversity Strategy to 2020, the Habitats and Birds Directives and the Water Framework Directive by applying GAP analysis, to complement available Copernicus information on the state and characteristics of rivers and riparian zones.

The action will develop an innovative toolkit (i.e. environmental knowledge and geo-information services) that will allow defining a selected set of standardized ecological indicators from both terrestrial and aquatic domains. This tool will enable achieving independent decision-making to assist on water resource management, restoration and conservation actions in these complex, fragile and valuable landscapes.

The action will also develop a benchmark for monitoring riparian processes and services (water quality, habitat conservation or urban planning) that will foster opportunities for European enterprises to provide innovative EO systems and services for a more sustainable management of riverscapes based on remote sensing data.

2 SELECTED REMOTELY SENSED INDICATORS

One of the main objectives of Cop.RIVER is to generate a list of remote sensing indicators relevant to the management and monitoring of riverscapes. First, a list of variables to characterize riverscape elements (terrestrial and aquatic domains) was generated after a careful analysis of the different EU regulations and directives and complemented with a literature review. Second, a list of remote sensing indicators was generated from a literature review, corresponding to each of the variables to characterize riverscape elements. Once the variables that define the riparian zone (terrestrial domain) conservation status and the remote sensing indicators that allow the measurement of the variables were identified, they were cross-referenced to show the list of indicators that can be used to define each variable. For the water quality (aquatic domain), methodologies derived from Sentinel-2 bands to measure parameters related to water quality parameter were identified using data from earlier experiences carried out by the IHCantabria team.

A summary table integrating the list of the variables to characterize riverscape elements, the remote sensing indicators, the corresponding methodologies and the suitability of the CLMS products to provide the necessary information to measure the variables previously identified has been produced for the terrestrial (Table 1) and aquatic (Table 2) domains. In addition, these tables integrate a series of columns indicating whether the variables are included in the different directives evaluated or not.

2.1 Terrestrial domain

For the terrestrial domain, a total of 229 monitoring variables were identified in the different EU regulations and directives and complementing information derived from the literature review. A series of riparian zones indicators based on remote sensing are listed in Table 1 with their respective references for calculating each variable, in addition to the Copernicus products that can provide, or partially provide, relevant information to measure each variable. Finally, it is indicated the directives and related guidelines that consider each of the variables for the characterization of the state of the riparian zones and the monitoring of their processes and services.

2.2 Aquatic domain

For the aquatic domain, a total of 7 monitoring variables were identified in the different EU regulations and directives and complementing information derived from the literature review. A series of water quality indicators based on remote sensing are listed in Table 2 with their respective references for calculating each variable, in addition to the Copernicus products that can provide, or partially provide, relevant information to measure each variable. Finally, it is indicated the directives and related guidelines that consider each of the variables for the characterization of the water quality and the monitoring of river processes and services.

Table 1. Summary of the terrestrial variables and indicators for riparian zones monitoring.

	Variable	Remote sensing indicators	CLMS Products Utility	WFD	HD	FD	BS2030	SNHBL	BGINs	NbS
Connectivity	Longitudinal connectivity	Narrowband hyperspectral Indexes (MSI, NMDI, WBI, NDWI, NDII, CAI, LCAI, PSRI, PRI, MCARI, MRENDVI, MRESR, MTVI1, MTVI2, RENVI, TCARI, TVI, VREI1, VREI2, ARI1, ARI2, CRI1, CRI2, NDLI and NDNI)[1] Topographic Indexes Derived from LiDAR (Elevation relative to low-flow water level, catchment area, catchment slope, topographic wetness index, multiresolution index of ridge top flatness, multiresolution index of valley bottom flatness, insolation and Topographic position index)[1] Structural metrics Derived from LiDAR (Height parameters, different percentiles of height distribution, cumulative percentage of returns in the different layers and intensity parameters and different percentage of intensity returned by points classified as ground)[1] Land cover[2] Riparian Zones Product[3]	Useful CLMS products: Riparian Zones Land Use/ Land Cover, Riparian Zones Green Linear Elements, CORINE Land Cover Products that may be partially of use: Tree Cover Density	YES	YES	NO	YES	NO	YES	YES
	Transversal connectivity			YES	YES	YES	YES	NO	YES	YES
	Transversal connectivity under the canopy			YES	NO	YES	NO	NO	NO	NO
	Others			YES	YES	NO	YES	NO	YES	YES

	Fragmentation	Fragstats landscape metrics[4][5][6] Land Use[6][7] Mean Nearest Neighbor[7] Road density[7] Area of forest (total core area index, class area and percentage of landscape)[7]	Useful CLMS products: Riparian Zones Land Use/ Land Cover, Riparian Zones Green Linear Elements, CORINE Land Cover Products that may be partially of use: Tree Cover Density, Imperviousness	YES	YES	NO	YES	NO	YES	YES
Disturbances	Artificial elements	Anthropic Exposure Indicator for River Basins (AEIRB)[8]	Useful CLMS products: None Products that may be partially of use: CORINE Land Cover, European Settlement Map, Imperviousness	YES	YES	YES	YES	YES	NO	YES
	Wildfires	Burned Area (BA) product MCD64A1 Collection 6[9] NDVI[10] NDWI[10] NBR[11][12]	Useful CLMS products: None Products that may be partially of use: Delineation of Riparian Zones, Normalized Difference Vegetation Index (NDVI), Seasonal Trajectories	NO	YES	NO	YES	YES	NO	NO
	Imperviousness	Satellite images based classification[13][14][15][16]	Useful CLMS products: Imperviousness Products that may be partially of use: Riparian zones Land Use/ Land Cover, CORINE Land Cover, Tree Cover Density, Normalized Difference Vegetation Index (NDVI), Fraction of Absorbed	YES	YES	YES	NO	NO	NO	YES

			Photosynthetically Active Radiation (FAPAR), Leaf area index (LAI), European Settlement Map							
	Floods	Hydrologic model[17] Daily Precipitation Analysis[17]	Useful CLMS products: None Products that may be partially of use: None	YES	YES	YES	NO	NO	YES	YES
	Eutrophication	Total nitrogen concentration (with Huan Jing-1 satellite bands combination) [18] Chl-a concentration (with SABI and NDWI)[19][20] Total phycocyanin (with R705 and R665)[21]	Useful CLMS products: None Products that may be partially of use: None	NO	YES	NO	YES	NO	NO	NO

	Drought	Forest: Canopy fluorescence yield[22] Forest Drought Response Index[23] Forest Vulnerability Index[24] River: Optimized Meteorological Drought Index (OMDI)[25] Standardised Precipitation index (SPI-3, 12 and 24)[26] Humidity Index in soil (iHI and iH-3)[26] Standardised Normalised Difference Vegetation Index (iNDVI and iNDVI-6)[26] modified Palmer Drought Severity Index (PDSI)[26][27] Water Deficit Drought Index (WDDI)[28] Standardized River Stage Index (SRSI)[29]	Useful CLMS products: None Products that may be partially of use: Normalized Difference Vegetation Index (NDVI)	NO	YES	NO	NO	NO	NO	YES

Species composition	Biodiversity	Height (Standard deviation of height)[30] Canopy cover[30] Canopy height density in different height ranges[30] Near infrared (NIR)[31][32] NDVI[32] Physiological reflectance adjusted index (PRI)[32] Anthocyanin reflectance adjusted index (ARI)[32] EVI[33]	Useful CLMS products: None Products that may be partially of use: Tree Cover Density, Normalized Difference Vegetation Index (NDVI)	YES	YES	NO	YES	YES	NO	YES
	Naturalness of the specific composition	LiDAR derived height parameters (H_{mean}, H_{sd}, H_{kurt}, H_{skew})[34] Coefficient of variation of echoes > 2m (H_{cv})[34] Canopy density (density of echoes > 50% of the 95_{th} percentile height to the total number of echoes)[34]	Useful CLMS products: None Products that may be partially of use: Tree Cover Density	YES	YES	NO	YES	YES	NO	YES

	Indicator species of regressive stages	Light intensity reaching the forest understorey[35] Elevation[36] Precipitations[36] Slope (steepness and exposure)[36] Annual potential insolation (API)[36] Compound topographic index (CTI)[36] Overstory plant species map[36] Spectral bands (Red edge 1 (RE1), 2 (RE2) and 3 (RE3), Short-wave infrared 1 (SWIR-1) and 2 (SWIR-2), Near infrared 1(NIR1) and 2 (NIR2))[37] Spectral indices (Chlorophyll Red-Edge (Chlred-edge), Visible Atmospherically Resistant Indices Red Edge (VARI-rededge), Normalized Difference 819/1649 (NDII2), Canopy Chlorophyll Content Index (CCCI), Carotenoid reflectance index 700 (CRI700), Normalized Difference 819/1600 (NDII), Modified Chlorophyll Absorption in Reflectance Index divided by the Optimized Soil Adjusted Vegetation Index (MCARI/OSAVI) and Normalized Difference NIR/Rededge Normalized Difference Red-Edge (NDRE))[37] Most suitable specific spectral band[38][39] NDVI[38][40] Canopy reflectance[41] Leaf and canopy water content[41] Pigment-related absorption features (reflectance derivatives)[41] Orthophotos[42]	Useful CLMS products: None Products that may be partially of use: Normalized Difference Vegetation Index (NDVI)	YES	YES	NO	YES	YES	NO	YES

		Δ pre-NDVI (NDVI pre flowering – NDVI blooming)[43] Δ pre-BR ((blue - red)/(blue + red) pre flowering) - ((blue - red)/(blue + red) blooming))[43] Δ pre-RG (((red - green)/(red + green) pre flowering) - ((red - green)/(red + green) blooming))[43] Δ BR-post ((blue - red)/(blue + red) blooming) - ((blue - red)/(blue + red) post flowering))[43] Δ RG-post (((red - green)/(red + green) blooming) - ((red - green)/(red + green) post flowering))[43] Soil Adjusted Vegetation Index (SAVI)[44] Perpendicular Vegetation Index-3 in the optimum bio window[44]								

	Good status indicator species	Single tree detection with WorldView-2 images[45]	Useful CLMS products: None Products that may be partially of use: None	YES	YES	NO	YES	YES	YES	YES
Age of canopy	Stand age	LiDAR derived height parameters[46][47][48][49][50] Crown closure between certain ranges of height[50] Tasseled Cap transformation brightness (TCB), greenness (TCG), wetness (TCW), angle (TCA) and distance (TCD)[51] Number of years since greatest change[51] Attributed change type[51] Topographic wetness index (TWI)[50][51] Topographic solar radiation index (TSRI)[51] Elevation[51] Slope[51] Texture (Mean intensity, Signal-to-noise value, First order variance, Kurtosis, First order entropy and Second order contrast)[52]	Useful CLMS products: None Products that may be partially of use: None	YES	YES	YES	YES	YES	NO	NO

	Regeneration	Difference between the NDVI and NBR indices[53] Forest Recovery Index (FRI)[54][55] Fraction of Vegetation Cover (FVC)[54][55] Indices derived from NDVI: Half recovery time (HRT), Recovery trend index (RTI) and Cumulative Relative Recovery Index (CRRI)[56] Elevation metrics derived from the Digital Terrain Model (DTM)[57] Vegetation cover derived from LiDAR NDVI[57] Landsat Structural index[58] Landsat Bands[59]	Useful CLMS products: None Products that may be partially of use: Normalized Difference Vegetation Index (NDVI)	YES	YES	NO	YES	YES	NO	YES

	Successional stages	Lorey's height (based on Skewness of Heights, Kurtosis of Heights, 90th height percentile and 6th height decile)[60][61] Gray Level Co-occurrence measures (GLCM) (Contrast, Variance, Mean and Dissimilarity)[60] Shadow fraction[60] Normalized Difference Moisture Index (NDMI)[62] Moisture stress index (MSI)[62] Inverse Minimum Noise Fraction (MNF) transformed bands [62] Tasseled cap transformation brightness (TCB) and wetness (TCW)[63]	Useful CLMS products: None Products that may be partially of use: None	NO	YES	NO	NO	NO	NO	YES
Land Use	Protected areas of community interest		Useful CLMS products: None Products that may be partially of use: Natura 2000	YES	YES	YES	NO	YES	NO	YES
	Land Use/Land cover		Useful CLMS products: Riparian Zones Land Use/Land Cover, Riparian Zones Green Linear Elements, CORINE Land Cover Products that may be partially of use: Delineation of Riparian Zones, Tree Cover Density, Imperviousness	YES	YES	YES	YES	YES	NO	YES

	Vegetation cover on the river bank	Land use land cover[64][65] MODIS product Vegetation Continuous Fields[66]	Useful CLMS products: Riparian Zones Land Use/Land Cover, Riparian Zones Green Linear Elements, CORINE Land Cover Products that may be partially of use: Delineation of Riparian Zones, Tree Cover Density, Imperviousness, Normalized Difference Vegetation Index (NDVI)	YES	YES	YES	YES	YES	NO	YES

Dasometry	Height	Canopy height characteristics derived from LiDAR[51][67][68][69][70][71][72] Canopy cover fraction[67][73] Difference in years between sampling and LiDAR data collection date[67] Digital Elevation Model (DEM)[74] Digital Surface Model (DSM)[74][75] Spectral bands (SWIR1, Red, Green)[76] Spectral bands combination (NIR/Green, SWIR1/Red, SWIR2/NIR, SWIR1/Green, Red/Green, SWIR1/Green, SWIR2/SWIR1 and SWIR2/Red)[76] GSAVI (Green Soil Adjusted Vegetation Index)[76] NDII (Normalized Difference Infrared Index)[76] Distance of the beginning signal and ground peaks[48]	Useful CLMS products: None Products that may be partially of use: None	NO	YES	NO	YES	NO	NO	YES

	Vertical complexity	Digital Surface Model (DSM)[77][78] Foliage Height Diversity (FHD)[79] Effective number of layers (NoLs)[79] Sentinel-1 VV and VH backscatter coefficients[80] Surface reflectance of Sentinel-2 bands[80] RGB image[78] Digital Terrain Model (DTM)[78] LiDAR derived height parameters[81][82] Sentinel-2 indices: NDVI, NDWI1, NDWI2, NDre1, NDre2[74] PCA texture maps[74]	Useful CLMS products: None Products that may be partially of use: Normalized Difference Vegetation Index (NDVI)	YES	YES	NO	YES	NO	NO	NO

	Dead wood	Dead wood Potential (DWP)[83] Blue[84] Hue[84] Saturation[84] Height[84] Spectral bands combinations (Red to all band ratio and Blue Infrared Ratio)[84] NDVI[84][85] Red-green index[85] LiDAR derived percentiles of height[86] Height metrics derived from LiDAR[86][87] NPV (Non-photosynthetic vegetation)[88]	Useful CLMS products: None Products that may be partially of use: None	YES	YES	NO	YES	YES	NO	NO
	Stand density	Fractional vegetation coverage[89] Summing the segments that contained the centroid within the sample plot[90] Number of trees using the Digital Surface Model for the individual tree count[91] SWIR-1[92]	Useful CLMS products: None Products that may be partially of use: Tree Cover Density	YES	YES	NO	YES	YES	NO	YES

	Diameter	Canopy cover fraction[67] Height metrics derived from LiDAR[67][94] Difference in years between sampling and LiDAR data collection date[67] Crown Projection Area (CPA)[94]	Useful CLMS products: None Products that may be partially of use: None	NO	YES	NO	NO	NO	NO	YES

	Biomass	Height metrics derived from LiDAR[67][97][98][99][100] Canopy cover fraction[67][101] Difference in years between sampling and LiDAR data collection date[67] Temperature data (annual mean temperature and greater than 0℃ accumulated temperature data)[102] Mean rainfall data (PA)[102] Digital Elevation Model (DEM)[102] Slope data (ASP)[102] NDVI[102][103][104][105] Perpendicular Vegetation Index (PVI)[102] Ratio vegetation index (RVI)[102] Soil Adjusted Ratio Vegetation Index (SARVI)[102] Transformative Soil adjusted ratio vegetation index (TSAVI)[102] Fractional cover[102] Maximal Stand density index (SDI_{smax})[98] Aboveground volume-weighted mean wood density (WD_{sAGV})[98] Leaf Area Index (LAI)[100][101] SWIR-2[106][107] Textural measure image developed from spectral SWIR-2 (B7_W5_ME)[106] Pigment Specific Simple Ratio (PSSR)[108] Near Infrared Band[108] Fraction of Absorbed Photosynthetically Active Radiation (FPAR)[104] Chlorophyll content in the leaf (Cab)[104]	Useful CLMS products: None Products that may be partially of use: Tree Cover Density, Normalized Difference Vegetation Index (NDVI), Leaf Area Index (LAI)	NO	YES	NO	YES	YES	YES	YES

		Texture characteristics of Sentinel-1[104] VH and VV (backscatter coefficients for polarizations VH and VV of Sentinel-1B)[106] Canopy Chlorophyll Content (LAIcb) and Canopy Water Content (LAIcw)[107] Chlorophyll index calculated using red-edge bands (Clre)[107] SWIR Band[107] Entropy measure derived from the summer NDVI[107] Simple Ratio (SR)[108] Soil Adjusted Vegetation Index (SAVI)[108] ICR[105] Green[105] NDI45[109] Enhanced Vegetation Index (EVI)[109] Red[110] Sentinel band textures (contrast, correlation, variance, entropy and second moment)[110] Normalized Difference Water Index (NDWI)[111]									

Habitat condition	Habitat quality	Riparian Forest Composite indicator[45] Tree cover[112]	Useful CLMS products: None Products that may be partially of use: Tree Cover Density	NO	YES	NO	NO	YES	YES	YES
	Habitat width	Using the riparian forest patch detection process[113]	Useful CLMS products: None Products that may be partially of use: Riparian Zones Land Use/ Land Cover, Riparian Zones Green Linear Elements, Delineation of Riparian Zones, CORINE Land Cover, Tree Cover Density	YES	NO	NO	NO	NO	NO	NO
	Habitat size	Processing satellite images to get landscape metrics[114][115] Fragstats landscape metrics[116] Land cover[117]	Useful CLMS products: None Products that may be partially of use: Riparian Zones Land Use/ Land Cover, Riparian Zones Green Linear Elements, Delineation of Riparian Zones, CORINE Land Cover, Tree Cover Density	NO	YES	NO	NO	NO	NO	NO

River morphology	River flow	Width related parameters[118][119] Convert the drainage areas to discharges (from a DEM)[120] At-many-stations hydraulic geometry (AMHG)[121] Correlation between observed discharge and the ratio of a land pixel for calibration (C) and a water pixel for measurement (M) (C/M Method)[122] SWOT (Surface Water and Ocean Topography) VM (Virtual Mission) measurements[123] Remote Sensing Hydrological Station[124]	Useful CLMS products: None Products that may be partially of use: None	YES	YES	YES	NO	NO	NO	YES
	Vegetation	NGAI[125]	Useful CLMS products: None Products that may be partially of use: None	YES	YES	NO	NO	NO	NO	NO

	Channel features	Channel width: Bank–to–bank width at the cross section[126] Separate water and dry pixels from Sentinel-1 images[118] Digital Elevation Model (DEM)[127][122] By algorithm that progressively increased the centerline from the raw DEM until thresholds of elevation differences and slopes were reached[120] Distance between bank edges perpendicular to the centerline[128][129] Modified Normalized Difference Water Index (MNDWI)[128] Measured at bankfull (bank to bank) using Cartesian coordinate method in ArcGIS[130] Sinuosity: Sinuosity Index (SI)[128][131][132] Accurate delineation of a channel centerline[129] Channel Sinuosity (S)[133][134] Ratio of the linear distance (D) to the actual river length (I)[122] River gradient: Ratio of elevation difference (H) to the horizontal distance (L)[122] Channel slope: Centreline extracted from the raw LiDAR DEM[120] SWOT (Surface Water and Ocean Topography) VM (Virtual Mission) measurements[123]	Useful CLMS products: None Products that may be partially of use: None	YES	NO	NO	YES	NO	NO	NO

		River depth: SWOT (Surface Water and Ocean Topography) VM (Virtual Mission) measurements[123]								

	Typical structures	Rill: Photointerpretation of stereoscopic satellite images[135] Aerial photographs[136] Rills depth estimated using two moving mean filters[136] Visual interpretation of differences in coloration, tonality, texture, and shape[137] Riffles: Width related parameters[138] Influenced channel slope and wood abundance[138] Bars: Mask product of water and land[139] Surface reflectance[139] Sentinel-1 contour lines[140] Sandbars 3D shape[140] Wet-dry line[141] Mean high water line[141] Erosion scarp[141] Vegetation line[141] Modified Normalized Difference Water Index (MNDWI)[141] Near-Infrared band (NIR)[142]	Useful CLMS products: None Products that may be partially of use: None	YES	YES	NO	NO	NO	NO	YES

Phenology	Phenology	Enhanced vegetation index (EVI) time series (to measure SOS and EOS)[143][144][145][146] Normalized Difference Vegetation Index (NDVI) time series (to measure SOS and EOS)[145][147] Phenology Index (PI) (a combination between NDVI and NDII) (to measure SOS and EOS)[145] Leaf Area Index (LAI) time series (to measure SOS and EOS)[145][149] MERIS Terrestrial Chlorophyll Index (MTCI) time series (to measure SOS and EOS)[145] EVI2 (two bands EVI (without the blue band)) time series (to measure SOS and EOS)[145] Normalized Difference Water Index (NDWI) time series (to measure SOS and EOS)[145] Maximum temperature (close relation to senescence)[148] Start of foliage season (SFS) (based on NDVI time series)[148] Maximum of foliage season (MFS) (based on NDVI time series)[148] Optimal foliage/leaf senescence (OFS) (based on NDVI time series)[148] End of foliage season (EFS) (based on NDVI time series)[148] Length of foliage season (LFS) (based on NDVI time series)[148] Growing Season Index (GSI)[149] Length of season (LOS) (Based on EVI time series)[146] Amplitude (AMPL) (Based on EVI time series)[146]	Useful CLMS products: Normalized Difference Vegetation Index (NDVI), Seasonal Trajectories Products that may be partially of use: Plant phenology Index, Fraction of Absorbed Photosynthetically Active Radiation (FAPAR), Leaf Area Index (LAI)	NO	YES	NO	NO	NO	NO	NO

Functions	Shading of the active watercourse	Solar radiation[150][151][152] Leaf Area Index (LAI)[150] Mean Manning roughness coefficient[150] Land cover[151] Digital Surface Model (DSM) of first returns (including vegetation)[151] Canopy height model (via LiDAR)[152]	Useful CLMS products: None Products that may be partially of use: Leaf Area Index (LAI)	YES	NO	NO	NO	NO	NO	YES
	Erosion reduction	(nothing found)	Useful CLMS products: None Products that may be partially of use: None	NO	NO	NO	NO	NO	YES	YES
	Others		Useful CLMS products: None Products that may be partially of use: None	NO	NO	NO	NO	NO	NO	YES

Table 2. Summary of the aquatic variables and indicators for water quality monitoring.

Variable	Remote sensing indicators	CLMS Products Utility	WFD	HD
Oxygenation conditions	Sentinel B3 and B4 Bands[153]	Useful CLMS products: None Products that may be partially of use: None	YES	YES
Salinity	Sentinel Band B3[153] Landsat Band 1- Coastal/Aerosol (0.433–0.453 mm)[154] Landsat Band 2-Blue (0.450–0.515 mm)[154] Landsat Band 3 – Green (0.525–0.600 mm)[154]	Useful CLMS products: None Products that may be partially of use: None	YES	NO
Temperature	Level-2 Provisional Surface Temperature (pST) estimates derived from the Landsat 4–5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper Plus (ETM+)[155] Temperature metrics estimated using Landsat 7 ETM+ and Landsat 8 TIRS imagery with the Radiative transfer equation applied with atmospheric correction parameters from AtmCorr[156]	Useful CLMS products: None Products that may be partially of use: None	YES	NO
Nutrient condition	Total nitrogen concentration (with Huan Jing-1 satellite bands combination) [18]	Useful CLMS products: None Products that may be partially of use: None	YES	YES

pH	Sentinel B3 and B4 Bands[153]	Useful CLMS products: None Products that may be partially of use: None	YES	YES
Pollution	Sentinel-2 B3 and B4 Bands[153]	Useful CLMS products: None Products that may be partially of use: None	YES	YES
Eutrophication	Total nitrogen concentration (with Huan Jing-1 satellite bands combination) [18] Chl-a concentration (with SABI and NDWI)[19][20] Total phycocyanin (with R705 and R665)[21]	Useful CLMS products: None Products that may be partially of use: None	NO	YES

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