Making SENSE of the water value chain in Australia

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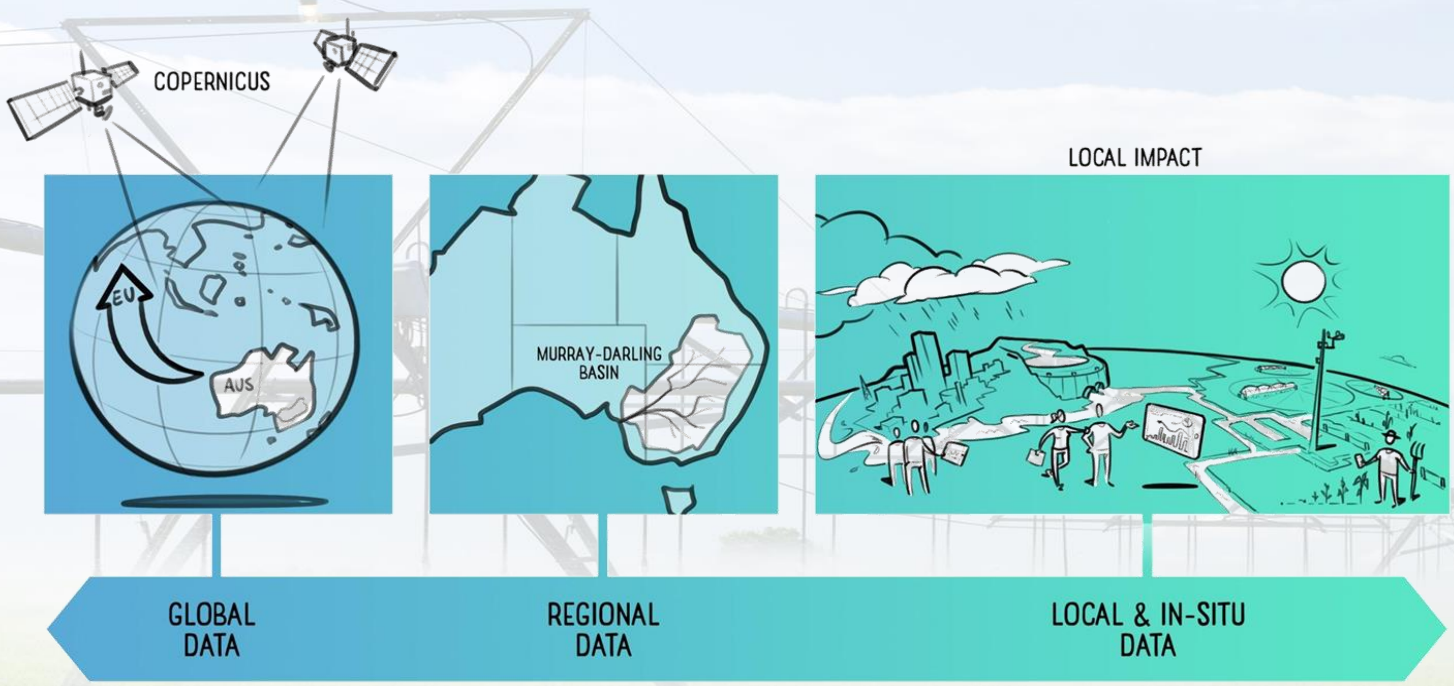
#MakingWaterSENSE

Newsletter 6 – July 2023



LinkedIn: Project WaterSENSE **Twitter:** @MakeWaterSENSE

This project has received funding from the Horizon 2020 research and innovation programme grant agreement No 870344

WaterSENSE consortium members

The WaterSENSE consortium consists of 7 partners: eLEAF BV (Netherlands), Hydrologic Research (Netherlands), Water Technology (Australia), Hidromod (Portugal), hydro & meteo (Germany), the University of Sydney (Australia) and HCP International (Netherlands).

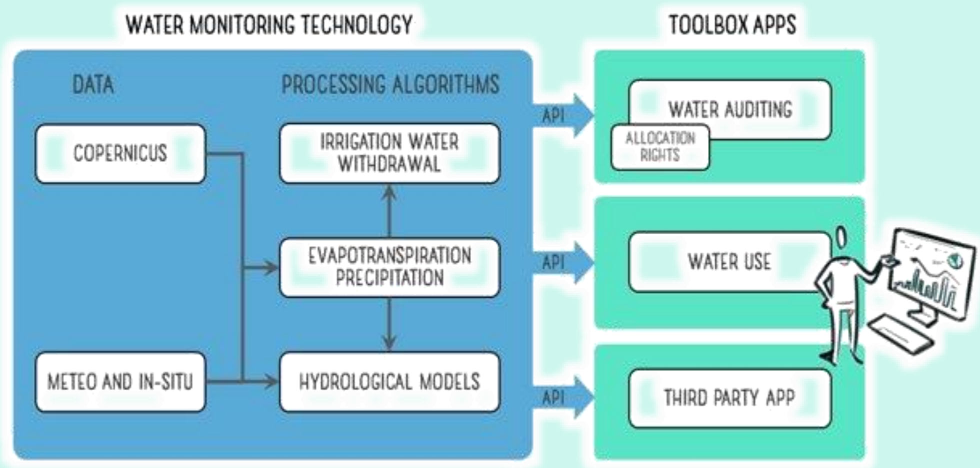
WaterSENSE Challenge

Deliver a modular approach to water accounting across the landscape:

- Observe water balance components using Remote Sensing (RS).
- At all scales (from “within field” scales to landscape/catchment scales).
- Crop water use, water storage, water application in a closed farm water balance.
- Vegetation condition, wetland flooding, quantifying environmental flow delivery.

WaterSENSE Project Objectives

- **Water Monitoring System:** Modular, operational, water monitoring system: Integrates Copernicus EO data, ground radar, models, in-situ data, and novel research.
- **Water Management Toolbox:** Makes data, algorithms and services available to users. Various Apps provide reliable, actionable Information.
- **Flexible Service Subscription models.**
- **Flexible Front Ends.**



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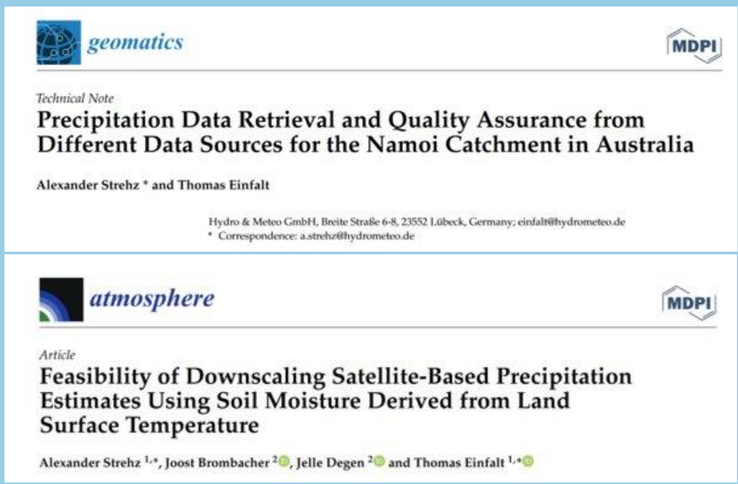
Research and Services Updates

Rainfall Data

WaterSENSE has studied the potential to downscale the existing IMERG Satellite rainfall data (near real time) to provide a spatial product at 1 km scale, using Satellite derived soil moisture (TOTRAM) and validating the results against the rain gauge adjusted radar rainfall data for the Namoi Radar (previously implemented in WaterSENSE).

Regrettably, the conclusion is that the use of this soil moisture data is not a feasible downscaling tool for rainfall.



geomatics MDPI

Technical Note

Precipitation Data Retrieval and Quality Assurance from Different Data Sources for the Namoi Catchment in Australia

Alexander Strehz * and Thomas Einfalt

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* Correspondence: a.strehz@hydrometeo.de

atmosphere MDPI

Article

Feasibility of Downscaling Satellite-Based Precipitation Estimates Using Soil Moisture Derived from Land Surface Temperature

Alexander Strehz [1,*], Joost Brombacher [2], Jelle Degen [2] and Thomas Einfalt [1,*]

Regional farm scale water balance pilot with the NSW DPE

NSW GOVERNMENT Planning & Environment

The WaterSENSE consortium has been requested by the NSW DPE to deliver a pilot farm water balance data and visualisation service using RS data across the 55JGG Sentinal 2 tile in Narrabri. This includes the provision of the following information per lot and farm dam on a weekly timestep:

- **Farm Gains:**
  - Gauge adjusted Radar rainfall data from the Narrabri Radar.
  - Incremental ET due to applied irrigation from eLEAF's HSP algorithm.
- **Farm Losses:**
  - Evapotranpiration (ET) from eLEAF's ETLook algorithm
  - Percolation from HidroMOD's HydroAquaFarm model
  - Runoff from HidroMOD's HydroAquaFarm model. Runoff is divided into two parts, the runoff potentially available for on farm retention and runoff losses.
  - Soil Water Content from HidroMOD's HydroAquaFarm model
- **Farm Dam Balance:**
  - Farm Dam area and change in area from Sentinel 2 derived Fisher Water Index data (other water detection algorithms can also be applied)
  - Farm Dam Volume and volume change, using dam area volume curves from the DPE.

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WaterSENSE

Contents lists available at ScienceDirect

Environmental Modelling and Software

journal homepage: www.elsevier.com/locate/envsoft

Volume and uncertainty estimates of on-farm reservoirs using surface reflectance and LiDAR data

Ignacio Fuentes, Richard Scalzo, R. Willem Vervoort

Contents lists available at ScienceDirect

Journal of Hydrology

journal homepage: www.elsevier.com/locate/jhydrol

Research papers

Towards near real-time national-scale soil water content monitoring using data fusion as a downscaling alternative

Ignacio Fuentes, José Padarian, R. Willem Vervoort

This information is being provided through the HydroNET Water Control Room. A screenshot of the HydroNET dashboard for the farm water balance is shown in Figure 1 below.

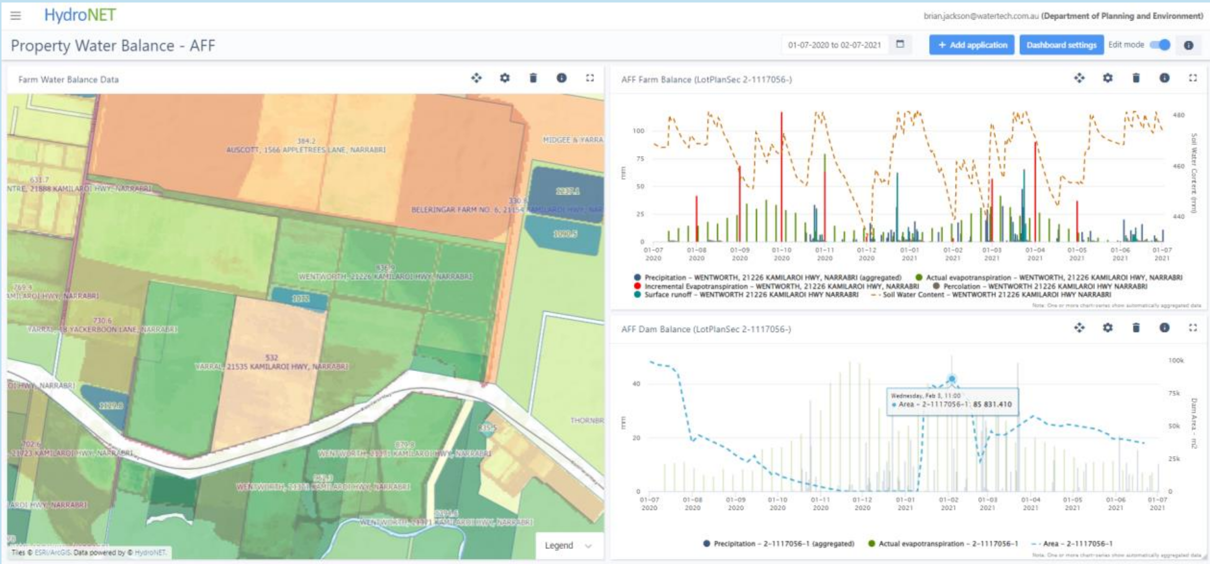

Figure 1: HydroNET dashboard for the WaterSENSE water use monitoring and farm water balance pilot service for the DPE.

HydroAquaFarm model

HIDROMOD have developed the new HydroAquaFarm model for the farm water balance service. HydroAquaFarm uses a deterministic approach to simulate the water at the parcel scale. The primary purpose of the model is to provide insight into the water balance of a given parcel and to help users understand the factors that influence water availability and water use. HydroAquaFarm calculates soil moisture, percolation, runoff, evapotranspiration and infiltration by using a set of numerical equations that describe the physical processes that govern water movement in the soil. HydroAquaFarm calculates the water volume balance in the soil using evapotranspiration, precipitation, crop coefficient, and irrigation as boundary conditions. The model considers evapotranspiration, percolation, and runoff losses as negative balance terms and precipitation and irrigation as positive balance terms. Refer to Figure 2 for a fluxogram of the model.

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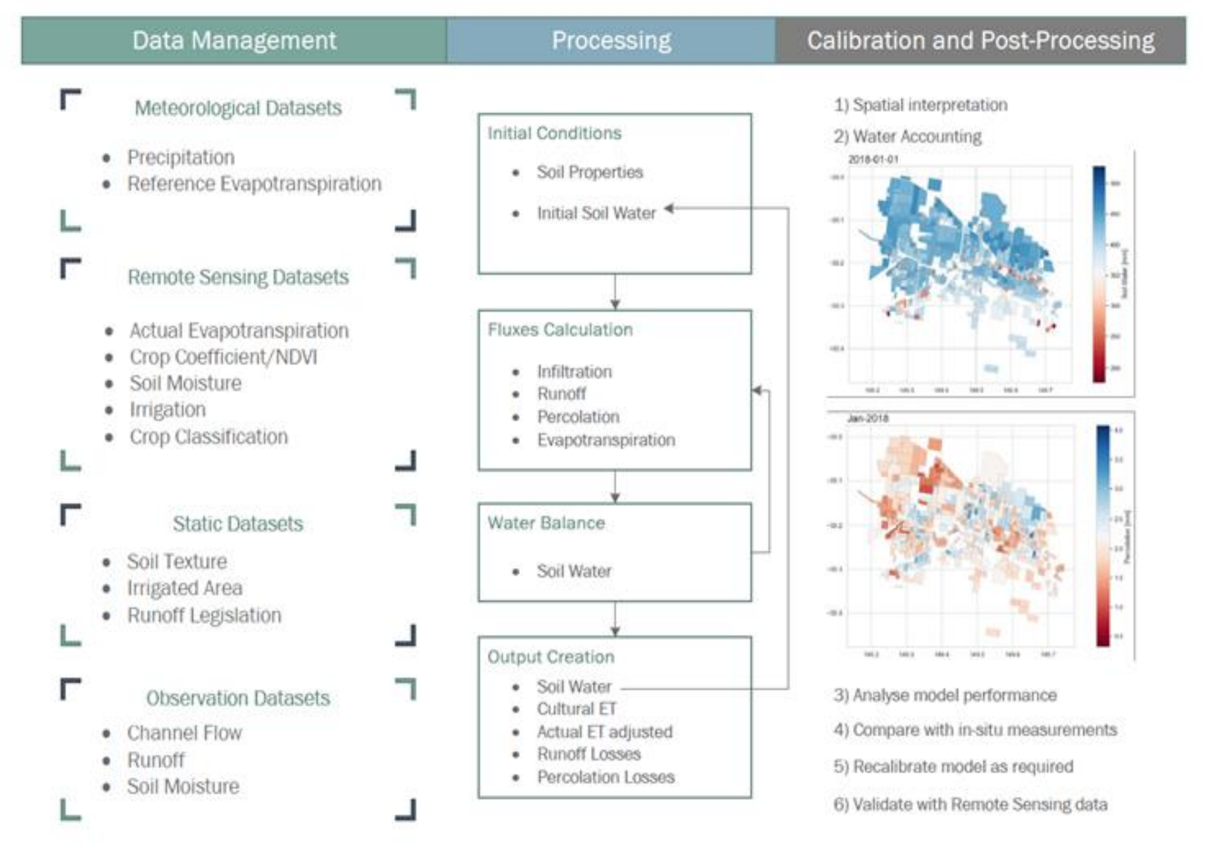

Figure 2: Fluxogram of the HydroAquaFarm model.

Updated ETLook algorithm for Evapotranspiration data

eLEAF has been working on creating a new cloud-based (AWS) data factory for global ET modeling at various resolutions (10m, 100m, 300 m) and are currently finalising the delivery of this ET data to the FAO WAPOR website.

ETLook algorithm overview:

The main strength of the ETLook model is that it tries to solve the energy balance (Figure 3), in contrast to many Kc-related ET models. The meteorological inputs used for the model, such as solar radiation, air temperature, vapor pressure, and wind speed, are mainly based on geostationary satellite observations and numerical weather models. **Evaporation and transpiration are also modeled separately**. To understand the evapotranspiration processes in high detail, **optical and thermal satellite observations are acquired**. The optical multispectral observations are provided by the Sentinel-2 constellation to ensure the highest spatial and temporal resolution. To include the effect of water stress on evapotranspiration, thermal satellite data from VIIRS is used and downscaled to produce a high-resolution rootzone soil moisture product. **The soil moisture product is subsequently converted into a stress coefficient**. Since optical and thermal remote sensing data is used, potential clouds need to be masked, which is done by a **machine-learning based cloud mask.**

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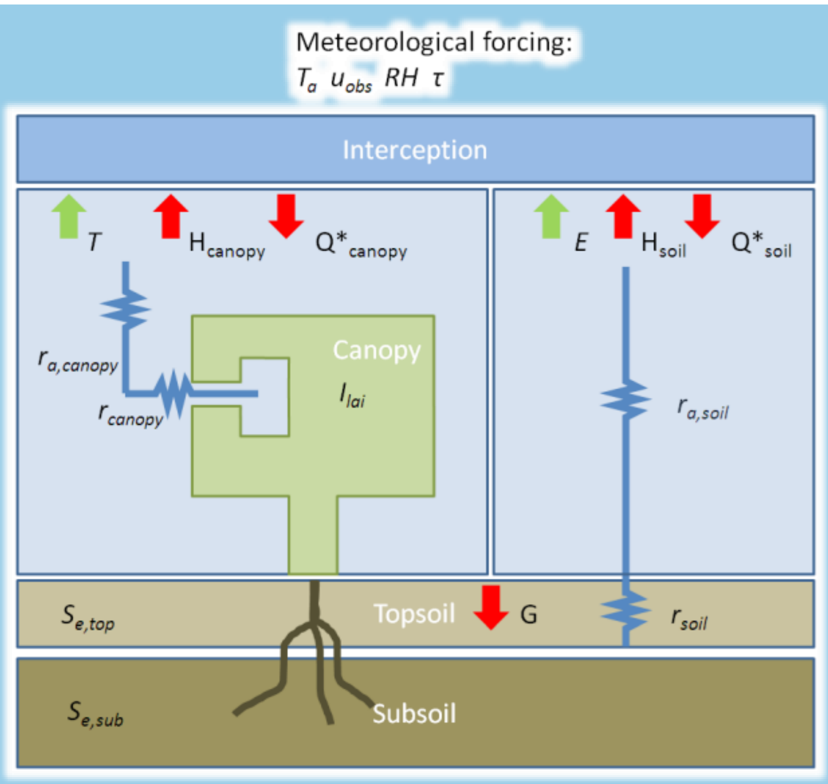

Figure 3: Schematic diagram illustrating the main concepts of the ETLook model, where two parallel Penman-Monteith equations are solved. For transpiration the coupling with the soil is made via the subsoil or root zone soil moisture content whereas for evaporation the coupling is made via the soil moisture content of the topsoil. Interception is the process where rainfall is intercepted by the leaves and evaporates directly from the leaves using energy that is not available for transpiration.

Global comparisons and validation

As part of the global ET data production and delivery to the FAO, eLEAF have conducted an initial soil moisture validation study for Africa and the Middle East using SMAP L4 data. Further to this, the ETLook model has been validated independently by IHE Delft as part of the FAO WaPOR program (Blatchford et al., 2020).

Initial comparisons in Australia

During the WaterSENSE project, the ETLook model has been compared with other available ET models for Australia (CMRSET and IrriSAT) for a single Sentinel 2 image tile covering Narrabri (55JGG). Further Validation is ongoing. A condensed summary of the initial comparison is provided below and in figure 4 and 5.

Initial comparisons show that for well-watered cropland, both models (ETLook & CMRSET) yield comparable results.

The **ETLook and CMRSET have different mechanisms to account for water stress. CMRSET relies on the global vegetation moisture index (GVMI)**. **ETLook's soil moisture model is based on the research of Yang et al. (2015) and is often referred to as the Thermal Optical Trapezoid Method (TOTRAM),** combining land surface temperature (LST) observations with NDVI.

For rainfed agriculture, especially in dry years, the GVMI produces much higher soil moisture estimates compared to the TOTRAM model. This results in less stress for the crop and therefore higher evapotranspiration estimates.

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GVMI is also acknowledged to be sensitive to bare soil, and the most optimal results are generated for pixels with a leaf area index (LAI) above 2 m^2/m^2 (Ceccato et al., 2002). CMRSET, therefore, tends to provide higher ET in dry areas with limited vegetation coverage as compared to ETLook.

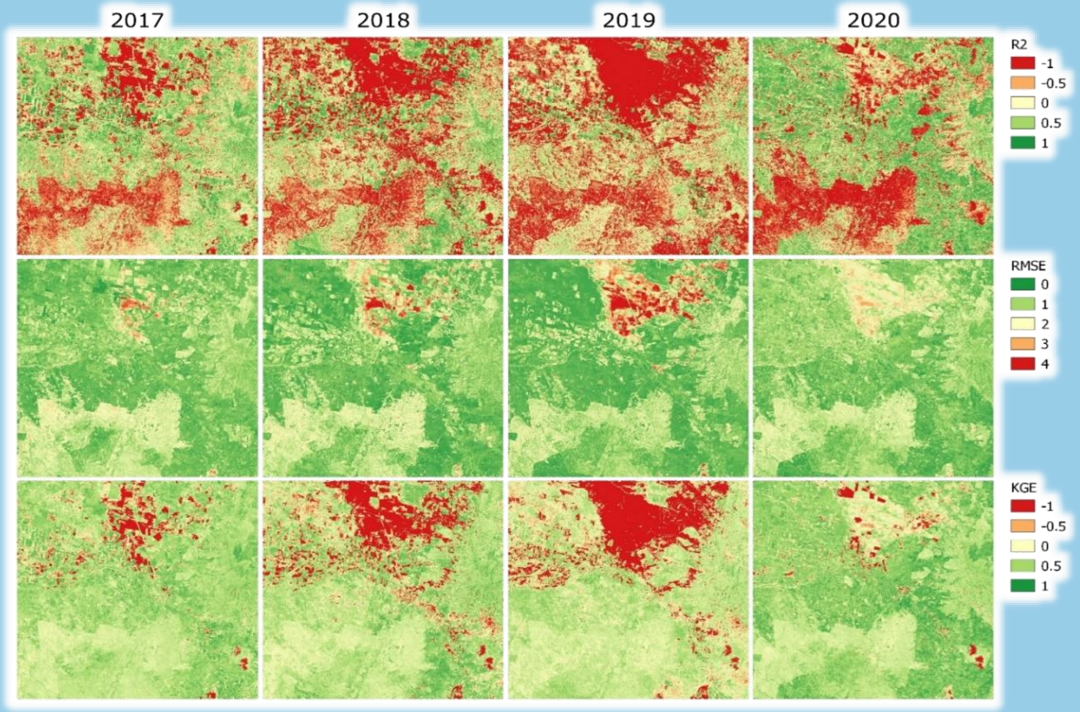

Figure 4: R2, RMSE, and KGE calculated for the comparison between ETa data from ETLook and CMRSET for each year separately during the 2017-2020 study period.

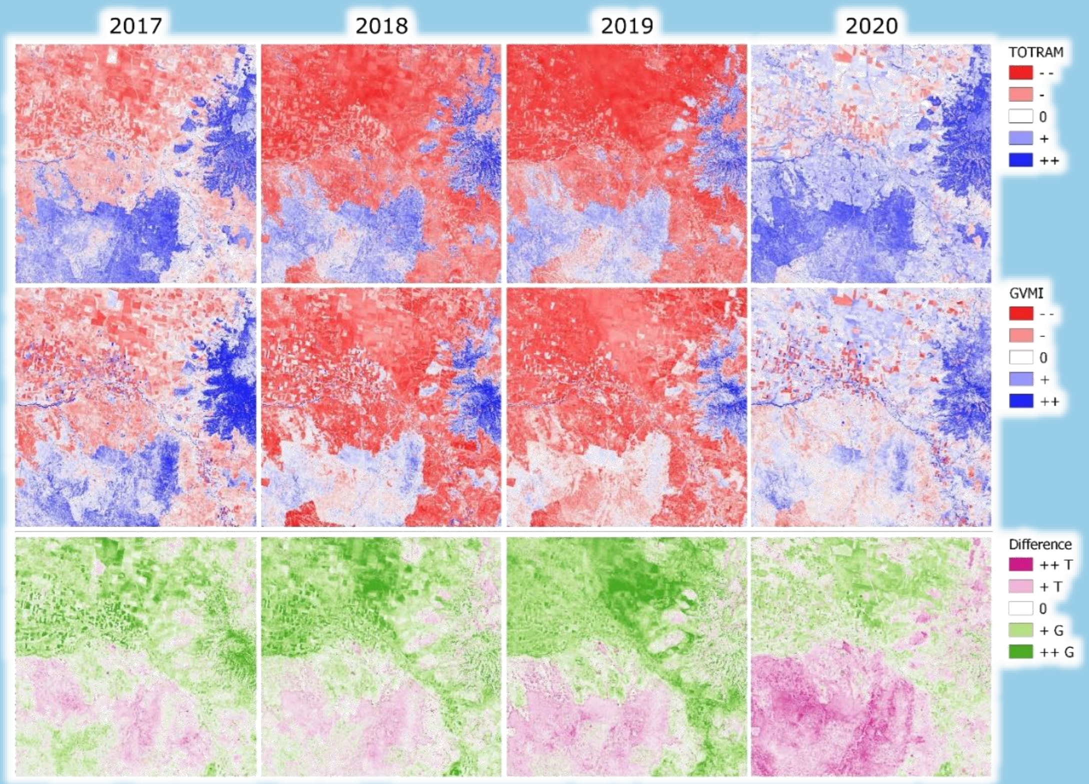

Figure 5: Comparison between ETLook's soil moisture model (TOTRAM) and CMRSET's soil moisture index (GVMI) per year for the 2017-2020 study period.

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Incremental ET due to irrigation – Improvements to the HSP model

A number of updates have been made to the Hydrologically Similar Pixels (HSP) model since the last newsletter.

Firstly, incremental evapotranspiration ($ETincr$) is now calculated for all agricultural pixels within a land cover mask, in contrast to only the irrigated agricultural pixels in the previous version. This change enables detection of irrigation outside known irrigated areas, which is important for detecting illegal irrigation, irrigation on new farms, or irrigation on previously rainfed farms.

Previous ETincr correction factor no longer applicable

However, the paramaterisation of the previous HSP model resulted in significant overestimation of irrigation for newly included rainfed agriculture pixels. The culprit was the correction factor applied to all natural vegetation pixels to artificially reduce the natural ET in the model. This correction was based on the assumption that you cannot directly compare the ET of natural vegetation against irrigated crops, as natural vegetation will generally have a deeper rooting depth than irrigated landuse, being more resilient to drought. The correction factor was implemented by setting the rooting depth of natural pixels to 1.5x that of irrigated landuse pixels. This changed the total available water in the model, which was subsequently used to correct the natural ET. Validation data from three different countries (Spain, South Africa, and Australia) showed that this correction yielded the most accurate water use estimates for irrigated crops.

Unfortunately, the rooting depth assumption is not valid for rainfed crops, as these crops will also have deeper rooting depths when compared to irrigated crops. The application of the same factor used previously for irrigated landuse pixels on rainfed agriculture pixels thus resulted in an artificial irrigation signal for the rainfed crops.

To mitigate this issue, eLEAF needed to find a way to differentiate irrigated from rainfed agriculture pixels and only apply a correction factor to irrigated pixels.

Instantaneous irrigated land use detection algorithm implemented

Previously, as explained in newsletter 5, the ETincr was used to generate irrigated area maps on an annual basis. However, this meant that we could only apply a revised correction factor after the end of the season, which is not too useful for clients.

We needed to be able to detect irrigation instantaneously, and we reverted to the HSP algorithm itself to do so. The HSP algorithm was initially set up to only compare the ET of irrigated and natural pixels. However, it can also be used to compare other kinds of datasets to understand the difference between irrigated and rainfed conditions. After some testing and literature research, **we settled on two datasets that can help us understand if a pixel is being irrigated or not**.

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The first dataset is ETLook's soil moisture product. This product is based on land surface temperature (LST) and NDVI and is used in the ETLook model to calculate the water stress of a crop. Since irrigation reduces water stress, there should be a difference in soil moisture content when comparing hydrologically similar natural and irrigated agricultural pixels. If this difference is positive, we mark this as a sign of a pixel being actively irrigated. In many cases, we found this to be true. However, we also saw that some agricultural areas near rivers also showed elevated soil moisture levels whilst no signs of irrigation could be seen from satellite images (Figure 6).

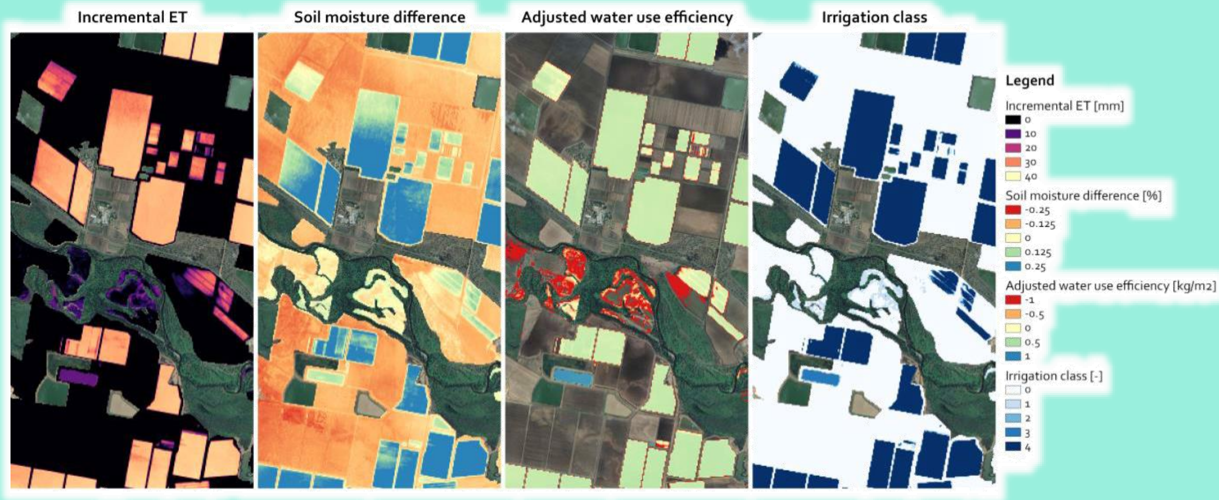

Figure 6: Overview of the incremental ET, soil moisture difference, and adjusted water use efficiency to produce irrigation classes on a weekly basis. Note that the area in the centre of the images are agricultural pixels near a river where no signs of irrigation are detected but still positive ETincr values are observed. The final irrigation class shows that when using the soil moisture difference and adjusted water use efficiency, these riverine areas are not being detected as irrigated agriculture anymore.

Therefore, we introduced a second dataset to account for these kinds of agricultural areas. This dataset relied on different versions of the water use efficiency. The water use efficiency is a product that is standard in the FAO WaPOR dataset, which is defined by dividing the total biomass or net primary production (NPP) by the actual evapotranspiration. However, this standard water use efficiency only tells you something about how efficiently the crop uses all the available water (rain + irrigation) to grow, yet we are mostly interested in the irrigated portion of the water use efficiency, which is normally very difficult to come by. Fortunately, since we have the HSP algorithm as a means to differentiate between rainfed and irrigated conditions, we were able to give an estimate of the irrigated water use efficiency.

Normally, irrigation systems are less efficient than rainfed agriculture in terms of water use. A poorer irrigation water use efficiency, therefore, means a higher likelihood of a pixel being irrigated. To translate these different versions of the water use efficiency to a proxy of irrigation likelihood, we derived the following equation:

$$AWUE = WUE_{agr} + WUE_{nat} - IWUE = \frac{NPP_{agr}}{ET_{agr}} + \frac{NPP_{nat}}{ET_{nat}} - \frac{NPP_{agr}}{ET_{incr}}$$

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With $NPPagr$ and $NPPnat$ as the net primary production [g/m2] and $ETagr$ and $ETnat$ as the actual evapotranspiration [mm] of the agricultural and natural pixel, respectively. $ETincr$ is defined as the difference between $ETagr$ and $ETnat$. The subsequently adjusted water use efficiency ($AWUE$) is a proxy for irrigated conditions. A positive $AWUE$ indicates that the sum of the total water use efficiency of the agricultural pixel ($WUEagr$) and the natural pixel ($WUEnat$) is larger than the irrigated water use efficiency of the agricultural pixel ($IWUE$), meaning that the agricultural pixel is not as efficient in using the irrigation water for biomass growth compared to using precipitation only. The more inefficient the irrigation system is, the higher the adjusted water use efficiency.

To create an instantaneous irrigated area map, we combine the $ETincr$ outputs with these two datasets to define five discrete classes. If the weekly $ETincr$ is above 20 mm, we immediately classify the pixel as irrigated agriculture (4). If the $ETincr$ is between 5 and 20 mm per week and both the soil moisture difference and adjusted water use efficiency are positive, we deem it highly likely that a pixel is being actively irrigated (3). If for the same $ETincr$ range the soil moisture difference is negative, we deem the likelihood of a pixel being irrigated to be moderate (2). If the soil moisture difference is positive but the adjusted water use efficiency is negative, irrigation is even more unlikely, and the high $ETincr$ might be introduced by agricultural pixels in riverine regions with abundant available water (1). Finally, if the $ETincr$ is below 5 mm per week, we do not see any sign of active irrigation (0).

From these classes, we eventually generate an irrigated area map (Figure 7). If the class is 4, we assign a pixel to be irrigated. Once a pixel is marked as being irrigated, we do not change the classification until the irrigation class becomes 0. If the irrigation class was 0 or 1 for the previous observation and the class of the current observation is 3, we assign the pixel to be potentially irrigated. If a pixel is being potentially irrigated for an entire season, but never marked as irrigated we assume there is abundant agricultural activity but limited use of irrigation.

New ETincr correction process using irrigation efficiency

Using the unadjusted $ETincr$ to estimate the irrigated water use of a farm showed a general underestimation. This underestimation was previously corrected with the mentioned correction factor, but since we now have an understanding of which pixels are irrigated, we can focus on other reasons why the $ETincr$ generally underestimates the total water use. The biggest difference between the water use observations of a water meter and our remote sensing based estimates is that we do not account for water losses during the irrigation activities due to open water evaporation, percolation, and runoff. We only observe the amount of irrigation water used by the crop for evapotranspiration processes. Therefore, we introduced the irrigation efficiency (%) to correct the $ETincr$ and generate more reliable outputs. In the literature, we found that for furrow irrigation in Namoi, the irrigation efficiency is typically around 70%. The newly adjusted $ETincr$ is calculated as follows:

$$ET_{incr,adj} = \begin{cases} \text{irrigated:} & \dfrac{ET_{incr}}{0.7} \\ \text{rainfed:} & ET_{incr} \end{cases}$$

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A quick validation using water meter data from 2017-2018 showed that the adjusted $ETincr$ does not heavily underestimate or overestimate the water use and is the most reliable result we have generated so far. Future research will focus on introducing a variable irrigation efficiency, depending on the irrigation type.

Figure 7: Two examples of an instantaneous irrigation mask for the first week of January (top) and the last week of February (bottom), 2023.

Open water detection and “growing” detected pixels under the trees

Challenges in using remote sensing to quantify surface water for environmental watering include:

- Cloud coverage
- Shadows

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- Vegetation canopy above the water
- Small water bodies with long perimeters compared to their area.

The University of Sydney is investigating the merits of a novel algorithm that uses DEM derived probability of depression (pdep) data to "grow" satellite-identified water patches to be hydrologically sensible and connected (Figures 8 and 9). The algorithm checks the adjacent pixels of the pdep map against threshold condition. If yes, a pixel is added to the region of the seed pixel as per the workflow below:

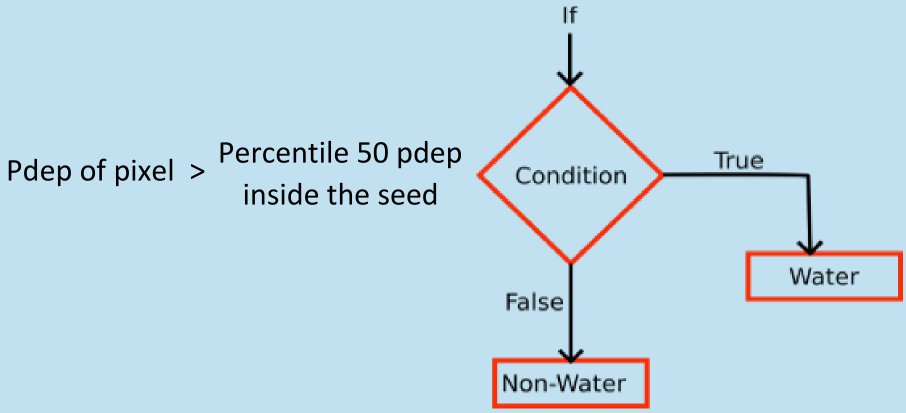

Figure 8: Probabilty of depression analysis workflow

This algorithm will be further verified and a paper is in production. The service is being demonstrated across the lower Goulburn River in collaboration with the Goulburn Broken CMA.

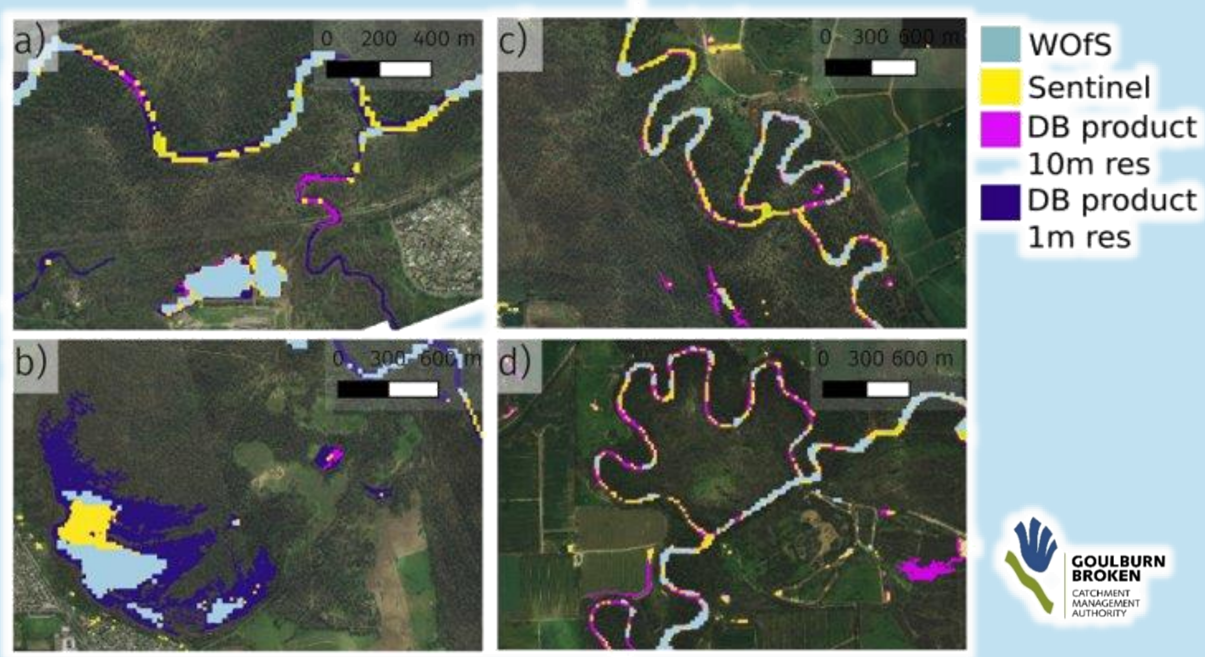

Figure 9: Rossi et al. in prep. Comparison of water detection from WOfS, Sentinel 2 (Fisher Index) and the pdep algorithm using 10m and 1m DEM data respectively.

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Vegetation condition parameters

We aim to provide timely information from remote sensing data and algorithms on the extent, health and water-use of wetland vegetation to support the impact of environmental flow releases on riparian and floodplain vegetation condition. Two parameters being explored across the lower Goulburn River in collaboration with the Goulburn Broken CMA are the Vegetation Condition Score (VCS) and the Biomass Production Score (BPS).

Vegetation Condition Score

VCS uses basic Biomass production data to assesses the current condition of vegetation condition by comparing the observed biomass to a cumulative probability plot of the long-term statistics (2017 to 2021 in the case of WaterSENSE) for the same week period (figure 10).

$$P = \frac{m}{n+1}$$

Where:
p is the probability of biomass value occurrence of a pixel
m is the rank of the biomass value for a pixel
n is the number of years involved in the analysis

VCS helps understanding:

- What the relative vegetation condition change over time is, independent of neighboring pixels.
- What areas are most affected by droughts, flow or other human activities, over a longer period.

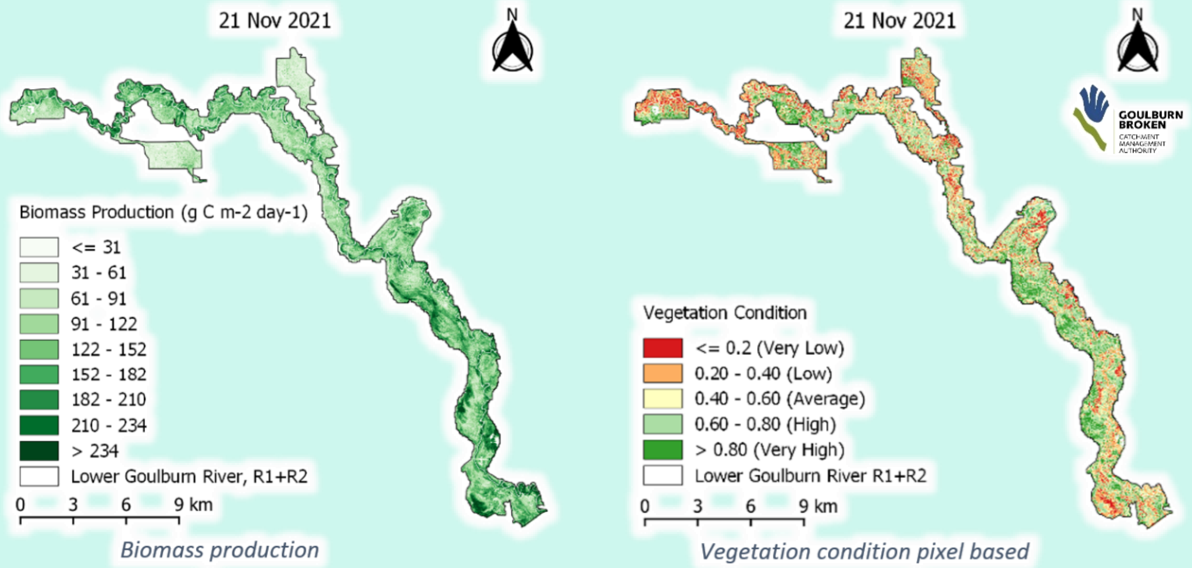

Figure 10: Biomass Production vs the Vegetation Condition Score, Goulburn river (Reach-1+2), 21 Nov, 2021

Vegetation Condition Score based on Ecological Vegetation Classes

Further insight can potentially be gained if the biomass data is aggregated to Ecological Vegetation Classes (EVC's) provided by the Department of Energy, Environment and Climate Action (DEECA, Victoria. These EVC's underpin the implementation of Victoria's Native Vegetation Management Framework, and the preparation of Regional Vegetation Plans.

WaterSENSE has thus conducted some initial comparisons of the VCS between EVC's. Comparisons within an EVC will be reported on in the next newsletter. The maps below (Figure 11) show vegetation condition based on vegetation class instead of pixels.

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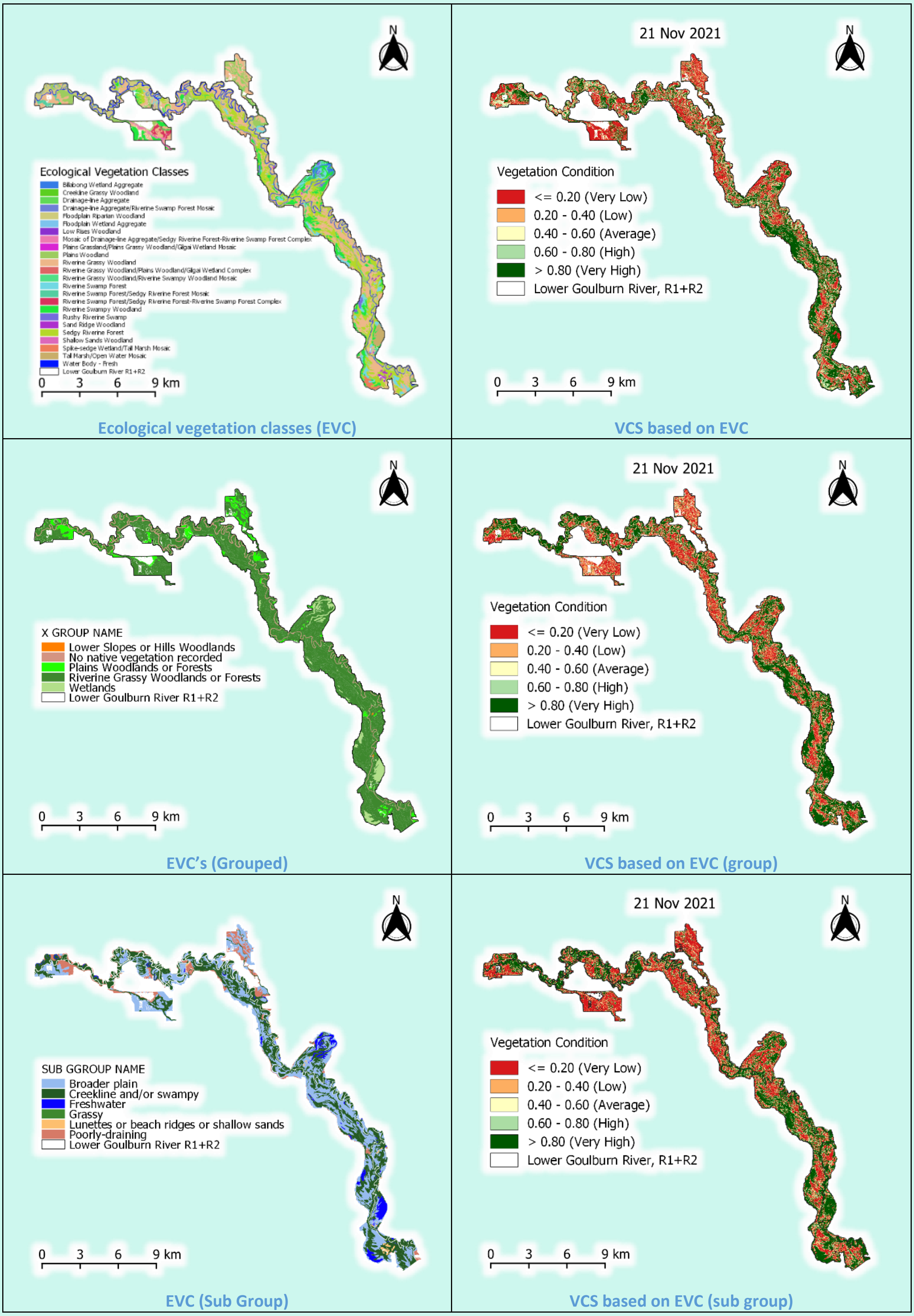

Figure 11: Vegetation condition based on vegetation class instead of pixels. The maps shows EVC's, their grouped classes, sub-grouped classes, and their corresponding vegetation condition maps for 21 Nov 2021.

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Figure 12 indicates that the average condition of Creekline Grassy Woodland is very low (0.2) while the condition of Drainage-line Aggregate/Riverine Swamp Forest Mosaic is very high. Figure 13 shows that the average condition of wetlands is highest while non-native vegetation has the lowest condition. Figure 14 demonstrates that poorly draining area has the lowest condition.

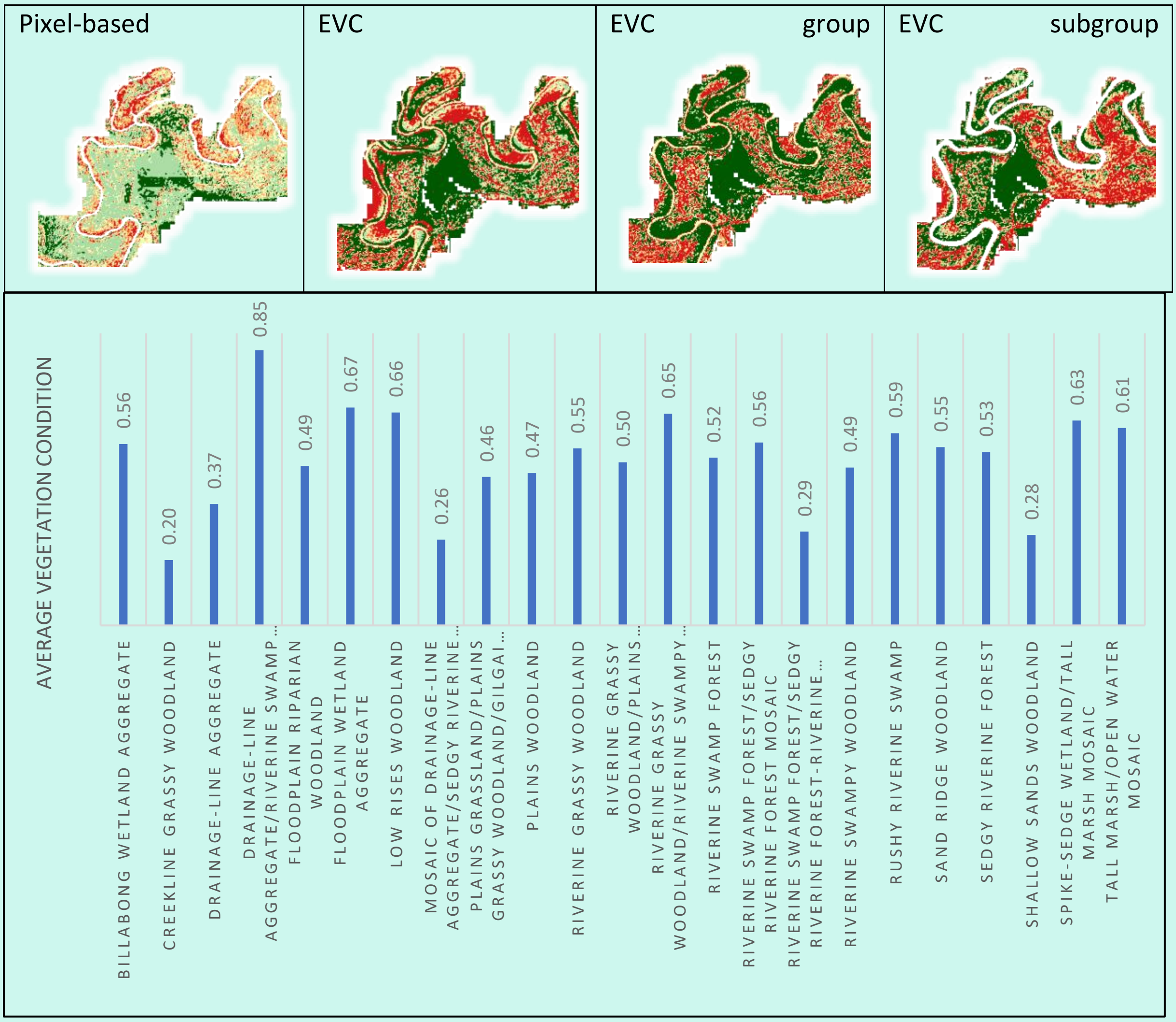

Figure 12: Average vegetation condition per ecological vegetation class, 21 Nov 2021

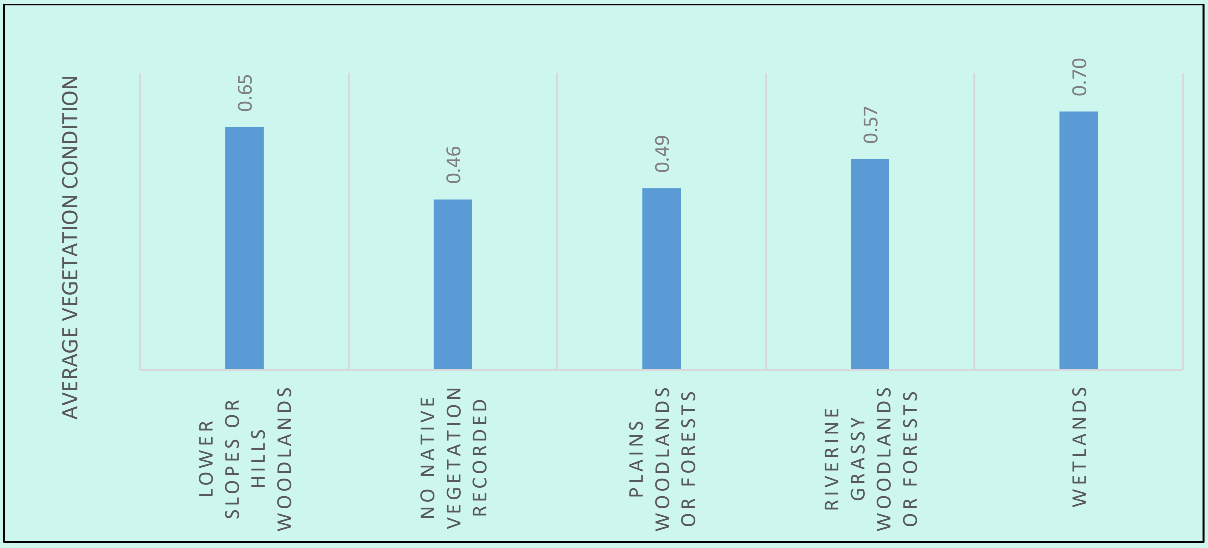

Figure 13: Average vegetation condition per ecological vegetation class (grouped), 21 Nov 2021

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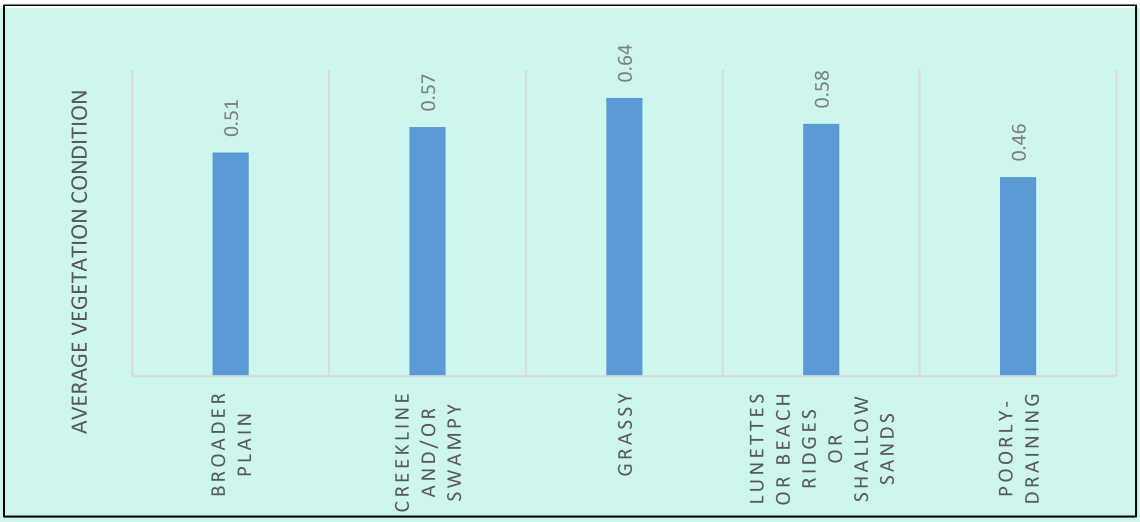

Figure 14: Average vegetation condition per ecological vegetation class (sub-grouped), 21 Nov 2021

Biomass Production Score

BPS scores biomass production of a pixel against a set benchmark (potential biomass production). BPS tells how a biomass production of a pixel performs in relation to other pixels in the area of interest.

$$BPS = \frac{B - B5}{B99 - B5}$$

Where:
BPS is biomass production score (-)
B is actual biomass production (g C m-2 day-1)
B5 is 5th percentile of biomass in the area of interest (g C m-2 day-1)
B99 is 99th percentile of biomass in the area of interest (g C m-2 day-)

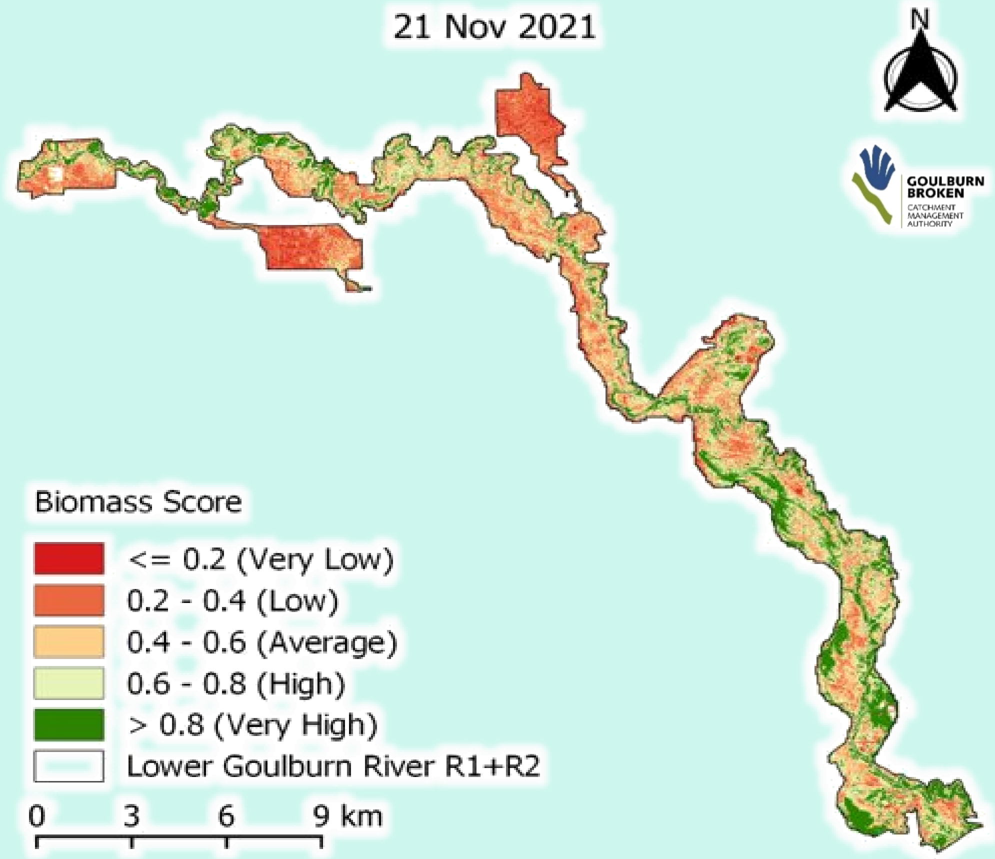

Figure 15: Biomass Production Score, Goulburn river (Reach-1+2), 21 Nov, 2021.

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BPS helps understanding:

- The performance of vegetation production of each pixel relative to other pixels (same vegetation type) in the area of interest (AOI).
- The spatial trends of biomass score (proximity to river or lake, upstream or downstream reach)
    - How the average performance of an AOI ichanges with the flow release.

Conferences

Since the previous newsletter , the WaterSENSE partners have attended and presented at the following Conferences (underlined names are WaterSENSE partner):

- **MODSIM 2023 – Darwin, Australia:**
    - WaterSENSE: Update on implementing Water Use Monitoring and Assessment Services. S. Wonink, B. Jackson, J. Brombacher, R.W. Vervoort, T. Einfalt, M. Alderlieste, P. Chambel Leitão, M. Noort, AR. Safi.
- **International SWAT Conference 2023 - Aarhus, Denmark:**
    - Operational Hydrological Models for Water Management: Case Studies from Australia, Brazil, and Portugal. P. Chambel Leitão, M. Alderlieste, B. Jackson.
- **Flood Management Australia 2023 - Sydney, Australia:**
    - The unexpected use of the Goulburn Broken Community Flood Intelligence Portal – A Shepparton case study. J Leister, B Jackson, G Tierney, Y Zhu.
- **GEO (Group on Earth Observations) Symposium, June 13 - 14, Geneva, Switzerland**
- **GEO Open Data and Open Knowledge Workshop, June 15 - 16, Geneva, Switzerland**
    - M. Noort. Participated in the GEOGLoWS (GEO Global Water Sustainability) practical session, brifign attendees on WaterSENSE progress.

Research Update

List of Publications

Please find a list of published papers from WaterSENSE below:

- Ignacio Fuentes, Richard Scalzo, R. Willem Vervoort. **Volume and uncertainty estimates of on-farm reservoirs using surface reflectance and LiDAR data.** Environmental Modelling & Software, Volume 143, 2021, 105095. ISSN 1364-8152. https://doi.org/10.1016/j.envsoft.2021.105095.
- Strehz, Alexander, and Thomas Einfalt. 2021. **Precipitation Data Retrieval and Quality Assurance from Different Data Sources for the Namoi Catchment in Australia.** Geomatics 1, no. 4: 417-428. https://doi.org/10.3390/geomatics1040024T. Download here.
- R. Willem Vervoort, Ignacio Fuentes, Joost Brombacher, Jelle Degen, Pedro Chambel-Leitão, and Flávio Santos. **Progress in detailed water productivity analysis at global locations**.
- Ignacio Fuentes, Jos´e Padarian, R. Willem Vervoort. **Towards near real-time national-scale soil water content monitoring using 2 data fusion as a downscaling alternative.** Journal of Hydrology, Volume 609, 2022, 127705, ISSN 0022-1694, https://doi.org/10.1016/j.jhydrol.2022.127705.

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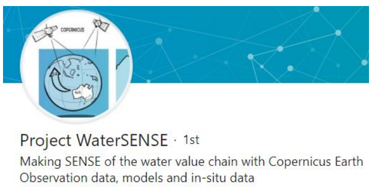

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This project has received funding from the Horizon 2020 research and innovation programme grant agreement No 870344