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Assimilation de données satellitaires pour le suivi des ressources en eau dans la zone Euro-Méditerranée

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## Résumé

Une estimation plus précise de l'état des variables des surfaces terrestres est requise afin d'améliorer notre capacité à comprendre, suivre et prévoir le cycle hydrologique terrestre dans diverses régions du monde. En particulier, les zones méditerranéennes sont souvent caractérisées par un déficit en eau du sol affectant la croissance de la végétation. Les dernières simulations du GIEC (Groupe d'Experts Intergouvernemental sur l'Evolution du Climat) indiquent qu'une augmentation de la fréquence des sécheresses et des vagues de chaleur dans la région Euro-Méditerranée est probable. Il est donc crucial d'améliorer les outils et l'utilisation des observations permettant de caractériser la dynamique des processus des surfaces terrestres de cette région. Les modèles des surfaces terrestres ou LSMs (Land Surface Models) ont été développés dans le but de représenter ces processus à diverses échelles spatiales. Ils sont habituellement forçés par des données horaires de variables atmosphériques en point de grille, telles que la température et l'humidité de l'air, le rayonnement solaire et les précipitations. Alors que les LSMs sont des outils efficaces pour suivre de façon continue les conditions de surface, ils présentent encore des défauts provoqués par les erreurs dans les données de forçages, dans les valeurs des paramètres du modèle, par l'absence de représentation de certains processus, et par la mauvaise représentation des processus dans certaines régions et certaines saisons. Il est aussi possible de suivre les conditions de surface depuis l'espace et la modélisation des variables des surfaces terrestres peut être améliorée grâce à l'intégration dynamique de ces observations dans les LSMs. La télédétection spatiale micro-ondes à basse fréquence est particulièrement utile dans le contexte du suivi de ces variables à l'échelle globale ou continentale. Elle a l'avantage de pouvoir fournir des observations par tout-temps, de jour comme de nuit. Plusieurs produits utiles pour le suivi de la végétation et du cycle hydrologique sont déjà disponibles. Ils sont issus de radars en bande C tels que ASCAT (Advanced Scatterometer) ou Sentinel-1. L'assimilation de ces données dans un LSM permet leur intégration de façon cohérente avec la représentation des processus. Les résultats obtenus à partir de l'intégration de données satellitaires fournissent une estimation de l'état des variables des surfaces terrestres qui sont généralement de meilleure qualité que les simulations sans assimilation de données et que les données satellitaires elles-mêmes. L'objectif principal de ce travail de thèse a été d'améliorer la représentation des variables des surfaces terrestres reliées aux cycles de l'eau et du carbone dans le modèle ISBA grâce à l'assimilation d'observations de rétrodiffusion radar $\left(\sigma^{\circ}\right)$ provenant de l'instrument ASCAT. Un opérateur d'observation capable de représenter les $\sigma^{\circ}$ ASCAT à partir de variables simulées par le modèle ISBA a été développé. Une version du WCM (water cloud model) a été mise en œuvre avec succès sur la zone Euro-Méditerranée. Les valeurs simulées ont été comparées avec les observations satellitaires. Une quantification plus détaillée de l'impact de divers facteurs sur le signal a été faite sur le sud-ouest de la France. L'étude de l'impact de la tempête Klaus sur la forêt des Landes a montré que le WCM est capable de représenter un changement brutal de biomasse de la végétation. Le WCM est peu efficace sur les zones karstiques et sur les surfaces agricoles produisant du blé. Dans ce dernier cas, le problème semble provenir d'un décalage temporel entre l'épaisseur optique micro-ondes de la végétation et l'indice de surface foliaire de la végétation. Enfin, l'assimilation directe des $\sigma^{\circ}$ ASCAT a été évaluée sur le sud-ouest de la France.

## Abstract

More accurate estimates of land surface conditions are important for enhancing our ability to understand, monitor, and predict key variables of the terrestrial water cycle in various parts of the globe. In particular, the Mediterranean area is frequently characterized by a marked impact of the soil water deficit on vegetation growth. The latest IPCC (Intergovernmental Panel on Climate Change) simulations indicate that occurrence of droughts and warm spells in the Euro-Mediterranean region are likely to increase. It is therefore crucial to improve the ways of understanding, observing and simulating the dynamics of the land surface processes in the Euro-Mediterranean region. Land surface models (LSMs) have been developed for the purpose of representing the land surface processes at various spatial scales. They are usually forced by hourly gridded atmospheric variables such as air temperature, air humidity, solar radiation, precipitation, and are used to simulate land surface states and fluxes. While LSMs can provide a continuous monitoring of land surface conditions, they still show discrepancies due to forcing and parameter errors, missing processes and inadequate model physics for particular areas or seasons. It is also possible to observe the land surface conditions from space. The modelling of land surface variables can be improved through the dynamical integration of these observations into LSMs. Remote sensing observations are particularly useful in this context because they are able to address global and continental scales. Low frequency microwave remote sensing has advantages because it can provide regular observations in all-weather conditions and at either daytime or night-time. A number of satellite-derived products relevant to the hydrological and vegetation cycles are already available from C-band radars such as the Advanced Scatterometer (ASCAT) or Sentinel-1. Assimilating these data into LSMs permits their integration in the process representation in a consistent way. The results obtained from assimilating satellites products provide land surface variables estimates that are generally superior to the model estimates or satellite observations alone. The main objective of this thesis was to improve the representation of land surface variables linked to the terrestrial water and carbon cycles in the ISBA LSM through the assimilation of ASCAT backscatter $\left(\sigma^{\circ}\right)$ observations. An observation operator capable of representing the ASCAT $\sigma^{\circ}$ from the ISBA simulated variables was developed. A version of the water cloud model (WCM) was successfully implemented over the Euro-Mediterranean area. The simulated values were compared with those observed from space. A more detailed quantification of the influence of various factors on the signal was made over southwestern France. Focusing on the Klaus storm event in the Landes forest, it was shown that the WCM was able to represent abrupt changes in vegetation biomass. It was also found that the WCM had shortcomings over karstic areas and over wheat croplands. It was shown that the latter was related to a discrepancy between the seasonal cycle of microwave vegetation optical depth (VOD) and leaf area index (LAI). Finally, the direct assimilation of ASCAT $\sigma^{\circ}$ observations was assessed over southwestern France.

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## List of Acronyms

| AMSR-E | Advanced Microwave Scanning Radiometer for EOS | GLDAS | Global Land Data Assimilation System |
| :---: | :---: | :---: | :---: |
| ASCAT | Advanced Scatterometer | GPP | Gross Primary Production |
| ASTER | Advanced Spaceborne Thermal Emission and Reflection Radiometer | HSAF | Hydrology Satellite Application Facility |
| AVHRR | Advanced Very High Resolution Radiometer | IAP94 | Institute of Atmospheric Physics |
| BATS | Biosphere-Atmosphere Transfer Scheme | ISBA | Interaction between Soil-BiosphereAtmosphere |
| CCDAS | Carbon Cycle Data Assimilation System | IBIS | Integrated Biosphere Simulator model |
| CCE | Competitive Complex Evolution | IPCC | Intergovernmental Panel on Climate Change |
| CDF | Cumulative Distribution Function | ISBA | Interactions between Soil, Biosphere, and Atmosphere |
| CGLS | Copernicus Global Land Service | JJA | June-July-August |
| CLM | Community Land Model | JULES | Joint UK Land Environment Simulator |
| CLVLDAS | Coupled Land Vegetation LDAS | LAI | Leaf Area Index |
| CNES | Centre National d'Etudes Spatiales | LDAS | Land Data Assimilation System |
| CNRM | Centre National de Recherches Météorologiques | LSM | Land Surface Model |
| CTRIP | CNRM-Total Runoff Integrating Pathways | LSV | Land Surface Variables |
| CYCLOPES | Carbon cYcle and Change in Land Observational Products from an Ensemble of Satellites | MAM | March-April-May |
| ECMWF | European Centre for Medium-Range Weather Forecasts | MCMC | Markov Chain Monte Carlo |
| ECVs | Essential Climate Variables | METOP | Meteorological Operational Satellite |
| ECUME | Exchange Coefficients from Unified Multicampaigns Estimates | MERIS | MEdium Resolution Imaging Spectrometer |
| Eos | Earth observations | MODIS | Moderate Resolution Imaging Spectroradiometer |
| EnKF | Ensemble Kalman filter | MOSES | Met Office Surface Exchange Scheme |
| ERA-5 | ECMWF Reanalysis 5th generation | MSI | Multispectral instruments |
| ERS | European Remote Sensing | MSS | Multi Spectral Scanner |
| ERTS | Earth Resources Technology Satellite | NASA | National Aeronautics and Space Administration |
| ESA | European Space Agency | NCA-LDAS | National Climate Assessment-Land Data Assimilation System |
| ETM | Enhanced Thematic Mapper | NDVI | Normalized Difference Vegetation Index |
| EUMETSAT | European Organization for the Exploitation of Meteorological Satellites | NIR | Near infrared |
| EURO- <br> CORDEX | Coordinated Downscaling Experiment - European Domain | NOAA | National Oceanic and Atmospheric Administration |


| EVI | Enhanced Vegetation Index | NSCAT | NASA Scatterometer |
| :---: | :---: | :---: | :---: |
| FAPAR | Fraction of the Photosynthetically Active Radiation absorbed by vegetation | NWP | Numerical Weather Prediction |
| FEWS NET | Famine Early Warning Systems Network | RFI | Radio Frequency Interference |
| FCOVER | Fraction of vegetation cover | PILPS | Project for Intercomparison of Landsurface Parameterisation Schemes |
| GCM | Global Climate Models | VV | Vertical polarization |
| GLC | Global Land Cover | SMOS | Soil Moisture and Ocean Salinity |
| PROBA-V | Project for On-Board AutonomyVegetation | SMOS- <br> MANIA | Soil Moisture Observing System Meteorological Automatic Network Integrated Application |
| OLCI | Ocean and Land Colour Instrument | SMMR | Scanning Multichannel Microwave Radiometer |
| ORCHIDEE | Organising Carbon and Hydrology in Dynamics Ecosystems | SNSB | Swedish National Space Board |
| RADSCAT | RadiometerScatterometer | SSM | Surface Soil Moisture |
| RBV | Return Beam Vidicon | SSTC | Scientific, Technical and Cultural Services |
| RCP | Representative Concentration Pathway | SURFEX | Surface Externalisée (externalized surface models) |
| RMSD | Root Mean Square Deviation | SWIR | Short Wave Infrared |
| SAR | Synthetic Aperture Radar | TEB | Town Energy Balance |
| SCE-UA | Shuffled Complex Evolution Algorithm | TIROS-1 | Television Infrared Observation Satellite |
| SEKF | Simplified Extended Kalman Filter | TM | Thematic Mapper |
| SDD | Standard deviation | VCI | Vegetation Condition Index |
| SiB | Simple Biosphere Model | VIS | visible |
| SIF | Solar Induced Fluorescence | VOD | Vegetation Optical Depth |
| SLA | Specific Leaf Area | VPI | Vegetation Productivity Index |
| SPOT | System for Earth Observation, "Système Pour l'Observation de la Terre | VWC | Vegetation Water Content |
| SPOT-VGT | Vegetation sensor on SPOT ('Système probatoire d'observation de la Terre' or 'Satellite pour l'observation de la Terre') satellite | WCM | Water Cloud Model |
| SMAP | Soil Moisture Active Passive |  |  |
| NLDAS | North American Land Data Assimilation System |  |  |
| NRCS | Normalized Radar Cross-Section |  |  |

## Introduction Générale

L'observation de la Terre depuis l'espace existe depuis plus de quarante ans. Elle devient une source de données primordiale pour l'étude du climat et pour la validation des modèles des surfaces terrestres, dans un contexte où les effets du réchauffement climatique sur l'environnement sont de plus en plus visibles. Le GIEC (Groupe d'Experts Intergouvernemental sur l'Evolution du Climat) nous alerte sur la forte probabilité d'un accroissement généralisé des aléas climatiques tels que les sécheresses, vagues de chaleur, précipitations extrêmes, feux de forêts, dans les années et les décennies qui viennent.

Ce constat est particulièrement alarmant pour la zone Euro-Méditerranée. L'initiative EURO-CORDEX (https://www.euro-cordex.net/) a permis d'améliorer les simulations climatiques utilisées par les experts du GIEC sur cette zone grâce à l'utilisation de modèles de climat régionaux. En particulier, la résolution spatiale de ces simulations climatiques est meilleure que les simulations climatiques classiques et peut atteindre $12,5 \times 12,5 \mathrm{~km}$. Les résultats de ces simulations climatiques publiés par Jacob et al. (2014) montrent, outre une augmentation de la température de l'air, un changement important dans le régime des précipitations, avec un accroissement en Europe Centrale et en Europe du Nord et une tendance à l'assèchement dans les régions plus proches de la Méditerranée. Ces tendances s'accompagnent d'un accroissement généralisé du nombre d'évènements de précipitations intenses en automne. Un autre résultat de cette étude est l'accroissement considérable au cours du $21^{\text {ième }}$ siècle du nombre de vagues de chaleur, pouvant aller jusqu'à plus de 40 évènements supplémentaires de mai à septembre à la fin du siècle (Figure i.1).

Cette évolution du climat a un impact sur les ressources en eau et sur l'agriculture. Certaines variables des surfaces terrestres permettant de caractériser l'impact du changement climatique sur les écosystèmes naturels et cultivés sont observables depuis l'espace. Il s'agit par exemple de l'indice de surface foliaire de la végétation « vrai» (LAI ou «true leaf area index» en anglais), de l'humidité superficielle du sol, et de l'albédo de surface. Cette dernière caractérise la part de rayonnement solaire réfléchi par la surface. Ces variables présentent une variabilité interannuelle, saisonnière, décadaire, voire journalière. Les données satallitaires ne représentant pas toutes les échelles spatiales et temporelles auxquelles se manifestent les effets du changement climatique, il est important d'associer les observations satellitaires à la modélisation des surfaces terrestres. La modélisation permet de comprendre les processus à l'œuvre à diverses échelles temporelles, d'assurer la cohérence entre variables, et d'accéder à des variables qui ne sont pas directement observables depuis l'espace, comme l'humidité du sol dans la zone racinaire.

L'adaptation au changement climatique est un sujet complexe comprenant de nombreux aspects socio-économiques. Elle doit avoir aussi une composante de suivi du climat et des évènements climatiques extrêmes qui repose sur l'amélioration des systèmes d'observation et des systèmes d'alerte. L'observation spatiale a un rôle important à jouer dans la mise en œuvre d'un suivi des surfaces terrestres à l'échelle mondiale et aussi à
l'échelle régionale grâce à des observations à plus haute résolution spatiale. L'évaluation de l'intégration de nouvelles observations dans les modèles des surfaces terrestres est nécessaire dans ce contexte.


Figure $\mathbf{i . 1}$ - Changement du nombre moyen de vagues de chaleur de mai à septembre sur la zone Euro-Méditerranée pour (en haut) 2021-2050 et pour (en bas) 2071-2100, par rapport à la période 1971-2000, à partir des simulations des modèles climatiques régionaux de l'initiative EURO-CORDEX pour deux scenarios climatiques (Representative Concentration Pathway (RCP) 4.5 et RCP 8.5, à gauche et à droite, respectivement). Les vagues de chaleur sont définies comme des périodes de plus de 3 jours consécutifs dépassant le percentile 99 du maximum journalier de la température de l'air de mai à septembre pour la période 1971-2000. Le RCP 4.5 est un scénario intermédiaire et le RCP 8.5 est le pire des cas. Adapté de Jacob et al. (2014).


Figure i. 2 - Intégration d'observations dans un modèle en utilisant l'assimilation de données (adapté de http://www.crm.math.ca/crm50/activites/activites-2019/assimilation-de-donnees/).

Il existe plusieurs méthodes permettant de fusionner les observations satellitaires et les modèles. La méthode la plus sophistiquée consiste à agir sur la physique du modèle et sur les simulations via l'intégration d'observations satellitaires. Il s'agit de l'assimilation de données (Figure i.2). Cette dernière peut-être utilisée pour déterminer plus précisément la valeur de certains paramètres du modèle ou bien pour corriger la trajectoire du modèle au fil de l'eau.

Le Centre National de Recherches Météorologiques (CNRM) a mis en œuvre un système d'assimilation de données (LDAS ou «land data assimilation system» en anglais) permettant de corriger la trajectoire du modèle ISBA (Interactions Sol-BiosphèreAtmosphère) au fil de l'eau en assimilant des produits satellitaires de LAI et d'humidité superficielle du sol. La mise en œuvre de cet outil à l'échelle mondiale est appelée «LDASMonde » (Albergel et al. 2017). Il s'agit d'un outil unique car l'assimilation du LAI permet de faire une analyse du contenu en eau du sol dans la zone racinaire, y compris en conditions sèches lorsque l'assimilation de l'humidité superficielle du sol n'apporte que peu d'information. LDAS-Monde est donc bien adapté au suivi des sécheresses et des vagues de chaleur (Albergel et al. 2019).

Les produits satellitaires assimilés par LDAS-Monde proviennent aujourd'hui du service Copernicus Global Land (https://land.copernicus.eu/global/). Le produit LAI «vrai » est élaboré à partir de données spatiales européennes SPOT-Végétation (Baret et al. 2013), PROBA-V et bientôt Sentinel-3. Le produit d'humidité du sol vient essentiellement des observations du radar diffusiomètre en bande C ASCAT. Il s'agit d'un instument des satellites météorologiques défilants européens METOP. Alors que le produit LAI est
disponible sur une période de plus de 20 ans, les données ASCAT ne sont disponibles que depuis 2007. Depuis peu, il existe une variante du produit d'humidité du sol à une résolution spatiale améliorée de $1 \mathrm{~km} \times 1 \mathrm{~km}$ grâce aux données du radar à synthèse d'ouverture («SAR» en anglais) en bande C du satellite Sentinel-1 (Bauer-Marschallinger et al. 2018) comme illustré dans la Figure i.3.


Figure i. 3 - Moyenne en août 2018 de l'indice d'humidité superficielle du sol sur l'Europe à une resolution spatiale de $1 \mathrm{~km} \times 1 \mathrm{~km}$ telle que dérivée de la combinaison des données en bande $\mathbf{C}$ du diffusiomètre ASCAT à basse résolution et du radar à synthèse d'ouverture (SAR) de Sentinel-1 (https://land.copernicus.eu/global/content/first-1km-soil-water-index-products-overeurope, dernier accès en septembre 2020), Bauer-Marschallinger et al. 2018.

Les produits satellitaires micro-ondes radar sont aujourd'hui essentiellement utilisés pour caractériser l'humidité du sol. Plusieurs études récentes ont cependant montré que les coefficients de rétrodiffusion radar ( $\sigma^{\circ}$ ) contiennent de l'information potentiellement utile pour caractériser la végétation (par exemple Vreugdenhil et al. 2016) au travers de l'épaisseur optique micro-ondes de la végétation (VOD pour « vegetation optical depth » en anglais). Cette variable VOD est reliée au LAI tout en incorporant d'autres caractéristiques
physiologues des plantes en relation avec leur contenu en eau. Un avantage considérable des $\sigma^{\circ}$ en bande $C$ est leur disponibilité par tout temps car le signal est peu affecté par l'atmosphère, les nuages en particulier. Le modèle ISBA permettant de simuler en même temps la croissance de la végétation et la variabilité spatiale et temporelle de l'humidité du sol, il est possible que l'on puisse simuler les $\sigma^{\circ}$ en bande C. Si cette condition est remplie, l'assimilation des $\sigma^{\circ}$ grâce à l'outil LDAS-Monde devient possible et peut être mise en œuvre en remplacement de l'assimilation de l'humidité superficielle du sol. Dans ce travail de thèse, de longues séries temporelles $\sigma^{\circ}$ en bande C issues des observations des instruments ASCAT sont analysées sur la zone Euro-Méditerranée et un opérateur d'observation est construit afin de permettre leur assimilation par le modèle ISBA. Une étude plus détaillée est menée sur le sud-ouest de la France (Shamambo et al. 2019).

Les objectifs de ce travail de thèse sont :

- D'évaluer la faisabilité de simuler les $\sigma^{\circ}$ en bande $C$ mesurés par les instruments ASCAT sur les surfaces terrestres à partir de variables pouvant être simulées par le modèle ISBA sur la zone Euro-Méditerranée,
- D'analyser l'influence d'éventuels facteurs perturbateurs du signal,
- De contruire un opérateur d'observation pour l'assimilation des $\sigma^{\circ}$ ASCAT par LDAS-Monde,
- D'analyser la répartition spatiale et temporelle des paramètres de l'opérateur d'observation,
- De comprendre la réponse des $\sigma^{\circ}$ ASCAT observés et simulés aux variables des surfaces terrestres telles que le LAI et l'humidité superficielle du sol,
- D'explorer la relation entre LAI et VOD, en particulier sur les zones cultivées,
- D'évaluer l'impact d'un changement rapide d'occupation du sol sur le signal en prenant l'exemple de la tempête Klaus de janvier 2009 dans la forêt des Landes,
- De mettre en œuvre l'assimilation des $\sigma^{\circ}$ ASCAT par LDAS-Monde et d'évaluer son impact sur les variables simulées par ISBA.

La Figure i. 4 résume les questions scientifiques qui ont été à l'origine de ce travail ainsi que la façon dont les objectifs de la thèse ont été atteints.

## Questions scientifiques

L'association de produits satellitaires et de simulations d'un modèle des surfaces terrestres est elle plus informative que chacune des sources diinformation considérée séparément sur la zone Euro-Méditerranée?

La télédétection radar en bande $C$ peut elle être utilisée pour le suivi de létat de la végétation?
Les coefficients de rétrodiffusion radar peuventils être directement assimilés dans un modele des surfaces terrestres?

## Construction d'un opérateur d'observation

$$
\begin{aligned}
& \Rightarrow \text { Sélection d̛une version du «Water Cloud Model »(WCM) qui soit capable de simuler les } \\
& \sigma^{\circ} \text { en bande CASCAT à partir de variables simulées par un modèle des surfaces terrestres } \\
& \Rightarrow \text { Analyse de linfluence déventuels facteurs perturbateurs du signal } \\
& \Rightarrow \text { Construire un opérateur d'observation pour l'assimilation des } \sigma^{\circ} \text { ASCAT dans un } \\
& \text { modèle des surfaces terrestres } \\
& \Rightarrow \text { Analyser la répartition spatiale et temporelle des paramètres de lopérateur d'observation } \\
& \Rightarrow \text { Comprendre la réponse des } \sigma^{\circ} \text { ASCAT observés et simulés aux variables des surfaces terrestres } \\
& \text { telles que le LAlet lhumidité superficielle du sol }
\end{aligned}
$$

## Mise en ceuvre du WCM

Zone Euro-Méditerranée

- Calage des paramètres du WCM
- Simulation des $\sigma^{\circ}$ et comparaison avec
les $\sigma^{\circ}$ observés parASCAT sur divers types
doccupation des sols

Etude de cas sur le sud-ouest de la France

- Etude plus détailée des paramètres du WCM et des facteurs perturbateurs du signal
- Evaluation de límpact dun changement rapide đoccupation du sol (tempête Klaus de jarnier 2009 surla forêt des Landes)
- Analyse de la relation entre LAI et VOD, en particulier surles zones cultivées


## Assimilation des $\sigma^{\circ}$ ASCAT dans un modèle des surfaces terrestres

Expérience d'assimilation séquentielle dans le sud-ouest de la France

- En ufilisant un filte de Kalman simplifí étendu comme technique đassimilation de données
- Evaluation des performances de lassimilation de données (jacobiens, incréments, analyse vs. openloop)
- Evaluation de limpact de lassimiation surle LAl et l'humidité superficiele du sol

Figure i. 4 - Vue analytique des sujets d'étude abordés dans ce travail.

L'effort a d'abord porté sur la contruction d'un opérateur d'observation, c'est-à-dire une extension du modèle ISBA lui donnant la possibilité de simuler les observations satellitaires de $\sigma^{\circ}$ en bande C. Il s'agit d'une étape indispensable avant de mettre en œuvre l'assimilation de données car le modèle ne peut assimiler que les observations qu'il est capable de représenter. En préalable à l'assimilation, l'opérateur d'observation a été mis en œuvre sur la zone Euro-Méditerranée. En particulier les valeurs des paramètres de l'opérateur ont été cartographiées. Une étude de cas sur le sud-ouest de la France a permis d'analyser plus finement les performances et les limites de l'opérateur.

Enfin, l'assimilation des $\sigma^{\circ}$ ASCAT dans ISBA a été mise en œuvre dans le sud-ouest de la France, à l'aplomb de stations météorologiques disposant de mesures de l'humidité du sol.

## General Introduction

Earth observation from space has been operative for more than forty years. It is now becoming a crucial source of observations for climate studies and for the validation of land surface models. This is particularly important in the current context, where climate warming impacts on environment are more and more visible. The IPCC (Intergovernmental Panel on Climate Change) has alerted us on the high probability of a general increase in the number of climate hazards such as droughts, heat waves, extreme precipitation events, forest fires, in the coming years and decades.

This alarming prediction is particularly severe for the Euro-Mediterranean area. The EURO-CORDEX initiative (https://www.euro-cordex.net/) has improved the climate simulations used by the IPCC experts over this area thanks to regional climate models. A remarkable achievement of these simulations is the enhanced spatial resolution with respect to the traditional climate models. It can reach $12.5 \times 12.5 \mathrm{~km}$. Apart from a general increase in air temperature, results from these climate simulations published by Jacob et al. (2014) show a marked change in the precipitation regime, with more rainfall in Central Europe and in northern Europe, and a trend towards dryer conditions in the regions close to the Mediterranean Sea. These trends come with a general increase in the number of extreme precipitation events during the autumn. Another result of their work is a marked increase durin the $21^{\text {st }}$ century of the number of heat waves, up to 40 more events per year from May to September at the end of the century (Figure i.5).

The evolution of the climate impacts water resources and agriculture. A number of land surface variables that can be used to characterize the impact of climate change on natural and cultivated ecosystems can be observed from space. These variables include, for example, the true Leaf Area Index (LAI), surface soil moisture, and surface albedo. The latter concerns the fraction of the incoming solar radiation that is reflected by the surface. These variables present an interannual, seasonal, weekly and even daily variability. Since the satellite data do not encompass all the spatial and temporal scales impacted by climate change, being able to combine satellite data with land surface models is needed. Modelling can be used in addition to observations in order to better understand processes across time scales, ensure the consistency between variables, and access variables that cannot be directly observed from space such as the root-zone soil moisture.

Adaptation to climate change is a complex topic involving many socio-economic aspects. Adaptation must also include a climate monitoring component. Monitoring extreme climatic events requires better observing systems and better warning systems. Remote sensing from space has a key role to play in the implementation of global land monitoring system and also at a regional scale thanks to observations at a better spatial resolution. In this context, progressing in the integration of new observations into land surface models is needed.


Figure i.5 - Change in the mean number of heatwaves from May to September over the Euro-Mediterranean area for (top) 2021-2050 and for (bottom) 2071-2100, with respect to the $1971-2000$ time period, as simulated by EURO-CORDEX regional climate models for two climate scenarios (Representative Concentration Pathway (RCP) 4.5 and RCP 8.5, left and right, respectively), with heatwaves defined as periods of more than 3 consecutive days exceeding the 99th percentile of the daily maximum temperature of the May to September season for the control period (1971-2000). RCP 4.5 and RCP 8.5 are intermediate and worst-case scenarios, respectively. Adapted from Jacob et al. (2014).


Figure i. 6 - Integration of observations into a model using data assimilation (http://www.crm.math.ca/crm50/activites/activites-2019/assimilation-de-donnees/).

Several methods can be used to merge satellite-derived observations and model simulations. The most sophisticated method consists in acting on the physics of the model and on the simulations through the integration of satellite-derived observations. This is called data assimilation (Figure i.6). The latter can be used to better tune model parameter values or to incrementally drive the model trajectory.

The National Centre for Meteorological Research (CNRM) has implemented a land data assimilation system (LDAS) in order to incrementally drive the ISBA (Interactions Soil-Biosphere-Atmosphere) model trajectory through the assimilation of satellite-derived LAI and surface soil moisture.

The tool used to implement this method at a global scale is called «LDAS-Monde» (Albergel et al. 2017). This tool has the unique capability of analyzing root-zone soil moisture through the assimilation of LAI observations, including in dry conditions when the assimilation of surface soil moisture has little impact on the deeper soil layers. LDASMonde is well suited to drought and heat wave monitoring (Albergel et al. 2019).

The satellite products that are now assimilated by LDAS-Monde are provided by the Copernicus Global Land service (https://land.copernicus.eu/global/). The "true" LAI product is derived from European satellite data from SPOT-Vegetation (Baret et al. 2013), PROBA-V and soon Sentinel-3. The soil moisture product is derived from the ASCAT Cband radar scatterometer. ASCAT is one of the instruments on board European low-orbit meteorological satellites METOP. While the LAI product is available for a long time period
of more that 20 years, the ASCAT data have only been available since 2007. A new version of the soil moisture product has emerged. It has an enhanced spatial resolution of $1 \mathrm{~km} \times 1$ km thanks to the Sentinel-1 C-band synthetic aperture radar (SAR) (Bauer-Marschallinger et al. 2018) as shown in Figure i.7.


Figure i. 7 - Mean surface soil moisture index in August 2018 over Europe at a spatial resolution of $1 \mathbf{k m} \times 1 \mathrm{~km}$ as derived from the combination of C-band low resolution ASCAT scatterometer and high resolution Sentinel 1 synthetic aperture radar (SAR) observations (https://land.copernicus.eu/global/content/first-1km-soil-water-index-products-over-europe, last access September 2020), Bauer-Marschallinger et al. 2018.

Satellite-derived radar microwave products are now mainly used to characterize soil moisture. Several recent studies have shown that radar backscattering coefficients ( $\sigma^{\circ}$ ) carry information on vegetation that could be used (e.g. Vreugdenhil et al. 2016), through the microwave vegetation optical depth (VOD). This VOD variable is related to LAI while incorporating other physiological characteristics of plants related to their water content. A key asset of C-band $\sigma^{\circ}$ observations is that they have an all-weather capability because the signal is not much affected by the atmopshere, clouds in particular.

Since the ISBA model is able to simulate plant growth and the spatial and temporal variability of soil moisture at the same time, simulating C-band $\sigma^{\circ}$ from ISBA outputs is feasible. If this is confirmed, the assimilation of $\sigma^{\circ}$ in ISBA thanks to the LDAS-Monde tool could be envisaged and implemented, as an alternative to the assimilation of surface soil moisture. In this PhD work, long time series of C -band $\sigma^{\circ}$ from ASCAT instruments' observations are analyzed over the Euro-Mediterranean area. An observation operator is built in order to allow the assimilation of C-band $\sigma^{\circ}$ into the ISBA model. A more detailed analysis is performed over southwestern France (Shamambo et al. 2019).

The objectives of this PhD work are to:

- Assess the feasibility of simulating the C-band $\sigma^{\circ}$ observed by the ASCAT instuments over land using land surface variables that can be simulated by the ISBA model over the Euro-Mediterranean area,
- Analyze the influence of possible perturbing factors of the signal,
- Build an observation operator for the assimilation of ASCAT $\sigma^{\circ}$ by LDAS-Monde,
- Analyze the spatial and temporal distribution of the parameters of the observation operator,
- Understand the response of observed and simulated ASCAT $\sigma^{\circ}$ to land surface variables such as LAI and surface soil moisture,
- Explore the relationship between LAI and VOD, in particular over agricultural areas,
- Assess the impact of a rapid land use change on the signal through the example of the Klaus storm of Janvier 2009 over the Landes forest,
- Implement the assimilation of ASCAT $\sigma^{\circ}$ by LDAS-Monde and assess its impact on the variables simulated by ISBA.

Figure i. 8 gives an overview of the scientific questions behind this work and of the rationale of the workplan design to reach the objectives of the thesis.

## Scientific questions

Is the combination of satellite-derived products and land surface model simulations more informative than each source of information alone over the Euro-Mediterranean area?

Can C band active remote sensing be used to monitor vegetation variables?
Can radar backscatter observations be directly assimilated in a land surface model?

## Building an observation operator

$$
\begin{aligned}
& \text { = Selection of a version of the Water Cloud Model (WCM) able to simulate ASCAT C band } \sigma^{\circ} \text { from } \\
& \text { variables simulated by a land surface model } \\
& \text { = Assess perturbing factors of the signal } \\
& \text { = Build an observation operator for the assimilation of ASCAT C band } \sigma^{\circ} \text { in a land surface model } \\
& \text { = Analyze the spatial and temporal distribution of the parameters of the observation operator } \\
& \text { = Understand the response of observed and simulated } \sigma^{\circ} \text { ASCAT to land surface variables such as } \\
& \text { LAl and suface soil moisture }
\end{aligned}
$$

## Application of the WCM

EuroMediterranean area

- Calbration of WCM parameters
- Simulation of $\sigma^{\circ}$ and comparison with
ASCAT $\sigma^{\circ}$ observations over varying
and cover types

| Case study over southwestem France <br> - More detaled analysis of WCM parameters and perturbing factors <br> - Evaluation of the impact of a rapid change in land use (Kaus storm of January 2009 in the Landes forest) <br> - Analysis of the reationship between LAI and VOD, particuarly in cultivated areas |
| :---: |
|  |  |
|  |  |
|  |  |

Assimilation of ASCAT C-band $\sigma^{\circ}$ in a land surface model
Sequential assimilation experiment in soutwestem France

- Using a Simpified Extended Kalman Fiter data assimikitoon technique
- Assessment of the data assimiation performance (Jacobians, increments, analysis vs. operloop)
- Assessment of the assimilation impact on LAl and sufface soi moisture

Figure i. 8 - Analytic view of the topics addressed in this work.

In a first stage, an effort was made to build an observation operator, namely an extension of the ISBA model for the simulation of satellite C -band $\sigma^{\circ}$. This step is required before implementing data assimilation because the model can only assimilate observations that can be represented by the model. Another step before the assimilation is the spatialization of the observation operator over the Euro-Mediterranean area. In particular, the operator parameter values were mapped. A case study over southwestern France was made in order to analyze more precisely the performances and the limitations of the operator.

Finally, the ASCAT $\sigma^{\circ}$ assimilation in ISBA was implemented in southwestern France above weather stations incorporating soil moisture observations.

## CHAPTER I - Scientific context

One of the major scientific challenges in relation to the adaptation to climate change is observing and simulating the response of land biophysical variables to extreme events. Land Surface Models (LSMs) constrained by high-quality gridded atmospheric variables are key tools to address these challenges. Modelling of terrestrial variables can be improved through the dynamical integration of observations. Remote sensing observations are particularly useful in this context due to their global coverage and frequent revisit. The current fleet of Earth observation missions holds an unprecedented potential to quantify Land Surface Variables (LSVs) and many satellite-derived products relevant to the hydrological and vegetation cycles are already available at high spatial resolutions. However, satellite remote sensing observations exhibit spatial and temporal gaps and not all key LSVs can be observed. LSMs are able to provide LSV estimates at all times and locations using physically-based equations. As in remotely sensed observations, LSMs are affected by uncertainties. Through a weighted combination of both remotely sensed observations and LSMs, LSVs can be better estimated than by either source of information alone. Data assimilation techniques enable one to spatially and temporally integrate observed information into LSMs in a consistent way to unobserved locations, time steps, and variables.

## 1 Interactions between terrestrial surfaces and the atmosphere

Extreme events are likely to increase in frequency and/or magnitude as a result of anthropogenic climate change (IPCC 2012, Ionita et al. 2017). In particular, simulations from IPCC (IPCC 2012) suggest that heatwaves and droughts in the Euro-Mediterranean region are likely to increase. Their impacts on ecosystems, agriculture, economy and health are considerable. It is therefore important to develop tools that can monitor and predict drought conditions (Svoboda et al. 2002, Luo and Wood 2007, Dai et al. 2011, Blyverket et al. 2019, Vogel et al. 2020) as well as their impact on land surface variables (LSVs) and society (Di Napoli et al. 2019). A major scientific challenge in relation to the adaptation to climate change is to observe and simulate how land biophysical variables respond to these extreme events (IPCC, 2012).

Having a practical understanding of the terrestrial water cycle is needed for estimating the impact of climate change and its variability on water scarcity or water excess in the Euro-Mediterranean area. Atmospheric and climate processes are affected by the land surface component of the water cycle. The latter impacts the spatial and temporal distribution of water, a key element for all processes related to life on terrestrial surfaces. Water and energy fluxes must be spatially and temporally well characterized because they are very useful to many scientific applications such as weather prediction, drought and flood monitoring, agricultural forecasting. Better knowledge of these processes is needed to characterize land-atmosphere interactions, predict and possibly mitigate climate change impacts.

Land surface models (LSMs) driven by high-quality gridded atmospheric variables and representing interactions between the soil-plant system and the atmosphere are key tools to address these challenges (Dirmeyer et al. 2006, Schellekens et al. 2017, Shukla et al. 1982, Koster and Suarez 1992, Beljaars et al. 1996, Drusch and Viterbo 2007, Koster et al. 2010). Initially developed to provide boundary conditions to atmospheric models, LSMs can now be used to monitor land surface conditions (Balsamo et al. 2015, Balsamo et al. 2018, Schellekens et al. 2017).

Additionally, the representation of land surface variables by LSMs can be improved by coupling them with models of other components of the Earth system such as atmospheric, ocean and river routing models (e.g. de Rosnay et al. 2013, de Rosnay et al. 2014, Kumar et al. 2018, Balsamo et al. 2018, Rodríguez-Fernández et al. 2019, Muñoz-Sabater et al. 2019).

However our understanding of the diverse interactions between water, carbon and energy cycles, climate and environment is hampered by the difficulty of representing accurately all land surface processes (Lahoz and de Lannoy 2014, Trenberth and Asrar 2014).

Earth observations (EOs) provide long-term and large scale records of land surface variables, which can complement LSMs. Satellite products are particularly relevant for the monitoring of LSVs. Satellite EOs related to the terrestrial hydrological, vegetation and energy cycles are now available globally, at kilometric scales and below (e.g. Lettenmaier et al. 2015, Balsamo et al. 2018). Combining EOs and LSMs can lead to enhanced
representation of the land surface conditions (e.g. Reichle et al. 2007, Lahoz and De Lannoy 2014, Kumar et al. 2018, Albergel et al. 2017, 2018a, 2019, Balsamo et al., 2018).

Integrating observations into LSMs covers several aspects:

- mapping of the model parameters used to characterize the representation of land properties within the model (e.g., soil properties, land cover),
- use of observations for model validation and evolution,
- dynamic integration of observations into models through data assimilation techniques.

This PhD study entitled "Assimilation of satellite data for water resources monitoring in the Euro-Mediterranean area" focuses on this third item. It aims at making use of data assimilation by combining satellite dataset and model simulation products in order to improve the monitoring of LSVs over the Euro-Mediterranean area.

The sections that follow outline the overall scientific context of this work.

## 2 Modelling land surface processes

Understanding and representing land surface processes as much as possible in LSMs is needed as these processes control the water and energy balances. As defined by Niu and Zeng (2012), land surface processes consist of biophysical and biogeochemical processes occurring within and over various land surface components and interacting with the atmospheric processes. These land surface processes act as one of the major factors controlling Numerical Weather Prediction (NWP) and climate model simulations (Ek et al. 2003, Pitman 2003, Flato et al. 2013). Since the implementation of the first LSMs describing land surface processes, developments have improved the representation of various phenomena involved in the transfer of energy, water, carbon and reactive gases fluxes between the surface and the atmosphere. The main phases of the evolution of land surface modeling are discussed in the following paragraph.

The first generation of models known as 'bucket model' (Manabe 1969) was established based on simple mass balance equations depicting water transfer. The bucket model showed no heat conduction into the soil, and had the same soil depth everywhere with fixed soil properties. The actual evaporation was limited by the ratio of the water content of the bucket to the bucket size. The water content exceeding the specified limit corresponding to the bucket size brought about surface runoff (Pitman, 2003). Plant stomatal conductance was not represented. The inconsistent behavior of the bucket model in Project for Intercomparison of Land surface Parameterisation Schemes (PILPS) has shown that the model was unable to represent diurnal to multi-annual scale surface hydrology (Liang et al. 1998, Wood et al., 1998). Despite their caveats, first generation models represented a major stride in the description of land surfaces processes in Global Climate Models (GCM).

In the 1980's, a new category of models termed second generation models emerged to further improve the representation of land surface processes (Deardorff 1978, Dickinson

1984, Sellers et al. 1986). These models are more complex in nature because they take into account the impact of vegetation on energy, water and momentum fluxes. They also contain several soil layers and represent specific soil properties allowing soil water interactions via the use of Richards equations-based water transfer (Sellers et al. 1997, Niu and Zeng 2012, Mohanty et al. 2016).

Second generation models integrate the representation of vegetation properties and a more or less complex representation of soil hydrology to estimate the energy and water fluxes. This category includes models such as the Noah LSM which is an improvement and is primarily based upon Deardorff 1978, BATS (Biosphere-Atmosphere Transfer Scheme, Dickinson 1984), SiB (Simple Biosphere Model, Sellers et al. 1986), IAP94 (Institute of Atmospheric Physics, Dai and Zeng 1997) or ISBA (Interaction between Soil, Biosphere and Atmosphere, Noilhan and Planton 1989, Noilhan and Mahfouf 1996). Usage of a second generation model by Beljaars et al. (1996) in a NWP context demonstrated that precipitation forecast was improved and Viterbo et al. (1999) also showed improved soil temperature predictions over Europe.

The advancement in the innovation allowed at the end of 1990's and in the years 2000 the introduction of third-generation models or LSMs. These models such as IBIS (Integrated Biosphere Simulator model, Foley et al. 1996), ISBA-A-gs (Calvet et al. 1998), MOSES (Met Office Surface Exchange Scheme, Cox et al. 1998), ORCHIDEE (Organising Carbon and Hydrology in Dynamics Ecosystems, Krinner et al. 2005), CLM (the Community Land Model, Oleson et al. 2010) and SiB2 (Simple Biosphere Model 2, Sellers et al. 1996) are mostly characterized by their capacity of simulating carbon uptake by plants and plant growth (Sellers et al. 1997 and Pitman 2003). Based on the work of Farquhar et al. (1980), these third-generation models were able to integrate a joint representation of stomatal conductance and photosynthesis into the representation of vegetation. The third generation models better describe plant physiology and phenology, and some also led to a better representation of snow by combining physically based multilayer snow sub-models with a parameterization of plant growth, liquid water retention and percolation (Jin et al. 1999, and Yang et al. 2003). Since third generation models are more realistic by using a photosynthesis-conductance scheme to couple the energy, water and carbon fluxes simultaneously, their development have extensively led to improving the description of biological and chemical processes, as theorized by Sellers et al. 1997.

## 3 Earth observations over land

Monitoring land surfaces variables is a fundamental requirement for environment studies, global climate and weather research (Lambin et al. 2001, Jung et al. 2006). Satellite observations have enabled the scientific community to improve ways of monitoring geophysical variables and phenomena of the land surface. Satellites can provide consistent data over the whole world, sending back information on areas lacking in situ observations.

Technological advances in instrument design of satellite sensors and the availability of free and open access satellite datasets for the scientific community has resulted into extensive ways of extracting information on land surface conditions. Frequent and
continuous measurements from space borne sensors are available for monitoring land surface processes.

The sub-sections below give an overall description of remote sensing of vegetation and surface soil moisture. It must be noticed that thermal infrared and hyperspectral techniques are not addressed because observations derived from such sensors were not used in this work.

### 3.1 Key milestones in the history of spatial remote sensing over land

Over the last 60 years, since the development of the Sputnik 1 artificial satellite in 1957 by the Soviet Union (Tatem et al. 2008), there has been an enormous evolution in the number of satellite missions that have been launched for different purposes including Earth observation. This has come in conjunction to an increase in computing capabilities. The trend in the number of Earth observations products is likely to increase further in relation to the increasing demand of geographic information. Currently, hundreds of Earth observing satellites are operating in orbit. They carry out measurements from different sections of the electromagnetic spectrum (e.g. visible, infrared and microwave spectral domains). The sensors on board Earth observation satellites are either passive or active depending on their specifications and intended usage. The passive sensors measure electromagnetic radiation that has been reflected or emitted from the atmosphere and the surface of the Earth. On the other hand, active sensors emit a signal and record the backscatter reflected back to the sensor from which information can be inferred about the observed surface.

The United States of America (USA) launched their first experimental satellite called Explorer 1 in January 1958 followed by Vanguard 1 in March 1958. After Vanguard 1, Vanguard 2 was launched which was specially implemented for Earth observation but due to technological failure, it only collected few data on cloud cover. It was replaced by TIROS-1 (Television Infrared Observation Satellite) in 1960, the first satellite to provide images of weather conditions from space. Due to the success of TIROS-1, many meteorological satellites were developed and also a variety of devices were specifically designed for land observation. The TIROS-1 was followed by a TIROS series leading to TIROS-N and to the National Oceanic and Atmospheric Administration (NOAA) series of satellites. The NOAA satellites contained an instrument called the Advanced Very High Resolution Radiometer (AVHRR) initially implemented for meteorological purposes. The AVHRR observations proved to be useful for land and sea surface monitoring. The latest generation of AVHRR instruments is used now on the EUMETSAT Metop low orbit meteorological satellites.

Following early research activities to evaluate the possibility of the use of Earth observation in forestry and agriculture, in 1972 the National Aeronautics and Space Administration (NASA) launched the Earth Resources Technology Satellite - ERTS (later renamed to Landsat 1 in 1975). The purpose of Landsat 1 was to study and monitor terrestrial areas. Since then, several Landsat series have been successfully launched enhancing the monitoring of the Earth system. Landsat series satellites carry several sensors such as RBV (Return Beam Vidicon) camera systems, MSS (Multi Spectral Scanner), and later TM (Thematic Mapper). The RBV camera system designed for Landsat 1 and 2 was used to acquire high resolution images of the Earth for a mapping application. The enhanced thematic mapper (ETM) is an eight band multispectral scanning radiometer capable of providing high-resolution imaging of 15 meters in order to give fine information of the

Earth's surface (Tatem et al. 2008, Loveland and Dwyer 2012). As significant advances in the scientific community continued to spread, more new sensors emerged with Earth observation applications. The French Space Agency (Centre National d'Etudes Spatiales (CNES)) launched the SPOT (System for Earth Observation, "Système Pour l'Observation de la Terre") series of satellite in 1986 with the help of SSTC (Belgian scientific, technical and cultural services) and the Swedish National Space Board (SNSB). SPOT has been developed to improve the monitoring and study of the Earth's surface. All SPOT satellites are in polar sun-synchronous orbit at an altitude of 830 km , producing a repeatability of 26 days.

In the 1990's, new multispectral remote sensing systems provided more possibilities to monitor the Earth's surface. An example of multispectral imaging system is the 14-band Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), one of the instruments onboard the US Terra satellite. The Terra satellite also included the MODIS (Moderate Resolution Imaging Spectroradiometer) instrument, more specifically designed for land applications. A second MODIS instrument was on board the Aqua satellite but morning observations from Terra were more efficient to retrieve vegetation variables than afternoon observations from Aqua (Tang et al. 2020). In Europe, the Vegetation instrument on board SPOT-4 and SPOT-5 was designed to observe LSVs and to monitor vegetation growth and senescence. Like MODIS and the latest version of the AVHRR instruments, SPOT-Vegetation included the SWIR (Short Wave Infrared) spectral band. The MEdium Resolution Imaging Spectrometer (MERIS) on board ENVISAT was designed for ocean studies. The heritage of MERIS is the OLCI (Ocean and Land Colour Instrument) instrument on board Sentinel-3 (see below).

In the 1970's, microwave remote sensing experiments were performed on board the Skylab space station (1973-74) using the S-194 L-band radiometer (Jackson et al. 2002), and the S-193 active and passive microwave instrument (RADSCAT) operating at Ku-band. Space borne active microwave systems such as scatterometers and imaging Synthetic Aperture Radars (SAR) gradually emerged together with the use of microwave radiometers. SAR systems are image producing radar sensors such as Seasat, ENVISAT, and Radarsat-1 (Ouchi 2013, Moreira et al. 2013). Scatterometers such as QuickSCAT, NASA Scatterometer (NSCAT) and the European C-band Advanced SCATterometer (ASCAT) are non-imaging radars useful for determining the wind direction over oceans (Figa-Saldaña et al. 2002). ASCAT sensors are part of the Metop series of European Earth observation satellites. They operate at a frequency of 5.2 GHz . It was shown that ASCAT data can provide information on the soil water content of terrestrial surfaces (Wagner et al. 2013). Spaceborne imaging microwave radiometers were first designed for ocean applications. However, the polarized signal extracted over land from SMMR (Scanning Multichannel Microwave Radiometer) data on Nimbus-7, from C-band ( 6 GHz ) to Ka-band ( 37 GHz ), was found to be related to land surface conditions (Choudhury 1989, Calvet et al. 1994). SMMR operated from 1978 to 1987. The next microwave radiometer including the C-band was AMSR (Advanced Microwave Scanning Radiometer). This instrument was onboard several platforms from 2002 to present. Missions based on L-band radiometry were implemented in the years 2010 for the purpose of monitoring surface soil moisture. The European Soil Moisture and Ocean Salinity (SMOS) mission (Kerr et al. 2001, Kerr et al. 2010, Kerr et al. 2016) was launched in November 2009. The US SMAP (Soil Moisture Active Passive) (Chan et al. 2016) was launched in January 2015. Both radiometers are still
providing data in 2020. It must be noticed that low frequency (e.g. L-band, C-band, X-band) radars and radiometers are not much sensitive to atmospheric effects and to clouds. They can be used in all weather conditions, either at day time or during the night. While L-band sensors are more sensitive to surface soil moisture and X-band to Ka-band sensors are more sensitive to vegetation water content, the signal measured by C-band sensors may be quite sensitive to surface soil moisture and to vegetation water content at the same time (Calvet et al. 2011).

The European Copernicus Sentinel family of satellites (Figure I.1) was recently designed for operational monitoring of the planet system. The first Sentinel missions (Sentinel-1, 2, and 3) can be used for terrestrial Earth Observation applications. The first series of the Copernicus Sentinel called Sentinel-1 was launched on 3 April 2014 and then followed by Sentinel-1B on 25 April 2016. The Sentinel 1 imaging C-band SAR (C-SAR, 5.4 GHz ) acquires information for land and ocean services at a high spatial resolution. After Sentinel 1, Sentinel-2 satellites consisting of Sentinel-2A and Sentinel-2B were launched on 23 June 2015 and on 7 March 2017, respectively. This second series of Sentinels are multispectral instruments (MSI) designed for monitoring land surfaces at a high spatial resolution. Following Sentinel 2, the Sentinel-3 mission was launched on 16 February 2016 for Sentinel-3A and on 25 April 2018 for Sentinel-3B. The purpose of this series of Copernicus Sentinels was for climate and environmental monitoring and also to support ocean forecasting. For land applications, Sentinel 3 can also be considered as a follow on of the European SPOT-Vegetation and PROBA-V missions. The Sentinel-4, 5, and 6 instruments are not yet in operations and concern atmospheric and ocean applications.


Figure I. 1 - Sentinel satellites of the Copernicus space program (https://gisgeography.com/sentinel-satellites-copernicus-programme/, last access 15 September 2020).

### 3.2 Monitoring land surface variables from space

### 3.2.1 Vegetation

Understanding vegetation behavior is essential because vegetation plays an important role in regulating the Earth carbon and water cycles. In particular, the Leaf Area Index (LAI) is a key driver of evapotranspiration (Simic et al. 2014). Earth observations from satellites provide extensive information about changes in vegetation over a vast range of temporal and spatial scales. The ability to extract information about vegetation dynamics from satellite sensors offers ways of studying and monitoring the vegetation phenology at a global scale. Since the launch of Landsat mission in 1972, the feasibility of studying the vegetation canopies from space was established. The monitoring of vegetation from space requires obtaining the electromagnetic wave reflectance information from the vegetation canopies using specific satellite sensors (Xue and Su 2017). These satellite sensors particularly used for obtaining information about the vegetation dynamics are made of bands within the visible $(0.40 \mu \mathrm{~m}-0.70 \mu \mathrm{~m}$ (VIS) ), near infrared ( $0.701 \mu \mathrm{~m}-1.3 \mu \mathrm{~m}$ (NIR)), and shortwave-infrared ( $1.301 \mu \mathrm{~m}-2.5 \mu \mathrm{~m}$ (SWIR)) spectral reflectance range. Figure I. 2 elaborates how various vegetation canopy types behave in terms of spectral signature across VIS, NIR, and SWIR wavelength bands.


Figure I. 2 - Reflectance of diverse plant canopies in the visible (VIS), near-infrared (NIR), and shortwave infrared (SWIR) wavelength bands (https://science.nasa.gov/ems/08 nearinfraredwaves, last access 15 September 2020).

Spectral reflectance of each vegetation canopy is determined by the morphological and chemical nature of the vegetation canopy considered (Chang et al. 2016, Zhang et al. 2012). In order to measure vegetation status using spectral reflectance of the vegetation canopy, different vegetation indices have been developed that can be directly estimated from reflectance observations. The reflectance of the vegetation canopy in regions of the VIS
domain is highly constrained by chlorophyll absorption in relation to the photosynthetic activity. It contrasts with the larger reflectance obtained in the NIR. Vegetation indices such as Normalized Difference Vegetation Index (NDVI) are directly estimated from reflectance observations. For vegetation biophysical variables like LAI, more complex methods are used to obtain them. Satellite missions such as MODIS provide LAI products since the year 2000 (Yang et al. 2006). In Europe, LAI products were derived from 1999 onward using SPOT-Vegetation data (CYCLOPES, Carbon cYcle and Change in Land Observational Products from an Ensemble of Satellites, Baret et al. 2007). The Copernicus Global land Service (CGLS) distributes global 10-day LAI products in near-real-time based on data from SPOT-Vegetation and PROBA-V using a machine learning algorithm developed by Baret et al. (2013).

### 3.2.2 Soil moisture

Soil moisture is a key LSV within the hydrological cycle as it influences both water and heat fluxes at the land-atmosphere interface (Shukla et Mintz 1982, Delworth et Manabe 1989, Brubaker and Entekhabi 1996, Pielke 2001, Legates et al. 2011). A very small fraction of only $0.0012 \%$ of the total amount of water on the Earth is contained in unfrozen soils (Chow et al. 1988). However, despite this small percentage, the importance of soil moisture in regulating processes related to the terrestrial water cycle such as water infiltration rate, runoff and evapotranspiration is crucial. Traditional ground-based approaches of measuring in situ soil moisture and other soil properties can be used (Calvet et al. 2016). However, these approaches are costly and time consuming. They are difficult to implement over large domains. Besides that, the local surface soil moisture is prone to rapid changes in both space and time hence making it very difficult to have accurate in situ measurements at all time and spatial scales (Leese et al. 2001). Both small scale and global precise evaluation of soil moisture on different temporal and spatial resolutions are necessary for the numerous applications of soil moisture monitoring. Advances in satellite remote sensing has enabled the feasibility of estimating the soil moisture variable on a large-scale and in remote areas where it was difficult to perform in situ measurements. Satellite missions such as SMOS and SMAP have been implemented with the purpose of soil moisture estimation on the Earth's surface. Due to availability of soil moisture datasets from satellite observations and LSMs, data assimilation of soil moisture observations in LSM has emerged for the past decades leading to improved representation of the hydrological variables such as evaporation, root-zone soil moisture and surface temperature (Houser et al. 1998, Zhang et al. 2005, Ni-Meister et al. 2006, Albergel et al. 2017).

### 3.2.3 Microwave remote sensing of soil moisture

Figure I. 3 shows the microwave frequency bands, ranging from 0.25 GHz to 111 GHz ( 120 cm to 0.3 cm in terms of wavelength, respectively). Low frequency (e.g. C-band, Sband, L-band, P-band) microwave remote sensing has advantages over other remote sensing techniques for soil moisture retrieval particularly because:

- vegetation is generally not completely opaque at these frequencies,
- measurements can be made in all weather conditions either during the day or at night.

The main reason microwave remote sensing is capable of providing soil moisture information is because there is a large difference between the dielectric permittivity of water and of the soil particles (Ulaby et al. 1982, and 1986, Shutko 1982, Njoku et Entekhabi 1996). Soil permittivity depends on soil moisture, soil texture, and on soil temperature to a
lesser extent. Retrieval of soil moisture from remotely-sensed microwave observations is primarily affected by soil texture and surface roughness. Over vegetated areas, vegetation optical depth and other vegetation properties can impact the observed signal (Wang 2018). Active and passive microwave sensors are two different approaches that are used to obtain information of soil moisture. Both of these approaches provide information on the surface reflectivity. The surface reflectivity comprises of the integral surface scattering coefficient over all scattering directions. The following sub-sections address passive and active microwave remote sensing for soil moisture retrieval.


Figure I. 3 - Microwave frequency bands (adapted from Ouchi 2013).

### 3.2.4 Passive microwave systems

Under passive microwave remote sensing, the natural thermal emission of land surfaces (or brightness temperature, $T_{\mathrm{B}}$ ) at microwave wavelengths is measured using a radiometer. Unlike the VIS or NIR spectral domain where reflected sunlight is the main source of radiation observed by passive sensors, the $T_{\mathrm{B}}$ signal measured by microwave radiometers at low frequencies mostly corresponds to the natural emission of the surface. Passive microwave remote sensing at high frequencies (e.g. Ka-band to W-band) has mainly applications for atmospheric observations used in weather forecast models.

Brightness temperature of soils is characterized by the soil microwave emissivity and soil temperature. Emissivity depends on dielectric permittivity of the soil and on soil roughness. The $T_{\mathrm{B}}$ observations allow for the estimation of soil moisture using retrieval techniques (Njoku and Entekhabi 1996). Major factors such as surface and subsurface heterogeneity (Tsang et al. 1975, Wilheit 1978, Kerr and Njoku 1990), soil surface roughness (Choudhury et al. 1989, Tsang and Newton 1982, Mo et al. 1987), soil texture and variability in soil temperature (Schmugge 1980, Dobson et al. 1985, Njoku et al. 1996) and soil surface roughness (Choudhury et al. 1989, Tsang and Newton 1982, Mo et al. 1987) affect the microwave $T_{\mathrm{B}}$. Despite diverse uncertainties caused by the factors mentioned above, the impacts of soil roughness and vegetation are smaller when dealing with long-wavelength (wavelength $\lambda>10 \mathrm{~cm}$ corresponding to L-band as shown on Figure I.3). In regions with low to moderate vegetation and considering the longer-wavelength region of the microwave spectrum (wavelength $\lambda>10 \mathrm{~cm}$ ) at L-band, the $T_{\mathrm{B}}$ is generally dominated by soil moisture (Wang and Choudhury 1995). In addition, vegetation and soil roughness have different spectral and polarization impacts on the soil brightness when compared to soil moisture, permitting the correction of perturbing factors through the use of
multi-polarization and multi-frequency measurements (Njoku and Entekhabi 1996). A vast number of algorithms have been developed (Jackson et al. 1993, Owe et al. 2001, Bindlish et al. 2003, Wen et al. 2003) for passive microwave soil moisture retrieval. Studies by Jackson et al. (1993), Wigneron et al. (1998), Du et al. (2000), Li et al. (2002), Aires et al. (2005), among others, have demonstrated the capacity of successfully using passive microwave sensors to measure soil moisture content.

### 3.2.5 Active microwave systems

Active remote sensing systems are not dependent on external sources of energy but provide their own electromagnetic energy that is sent from the sensor toward the surface of the object being measured. The backscattered signal from the measured surface is recorded by the sensor's receiver (Barrett et al. 2009, Kornelsen and Coulibaly 2013). Active microwave soil moisture retrieval has demonstrated considerable usefulness in many domains such as meteorology, hydrology and agriculture (Baghdadi et al. 2002, Seneviratne et al. 2010, Petropoulos et al. 2015). Perturbation from surface roughness and vegetation and limited swath width are some of the limitation of using active microwave sensors for soil retrieval (Liang et al., 2019). Active microwave systems can be divided under two categories: imaging sensors such as synthetic aperture radars and non-imaging sensors such as radar altimeters and scatterometers.


Figure I-4 - Active and passive microwave sensors (blue and red colors, respectively) used for the generation of the ESA CCI soil moisture data sets (https://www.esa-soilmoisture-cci.org, last access in September 2020).

### 3.2.6 Non-imaging radars

Under non-imaging active sensors, two distinct categories exist which are scatterometers and radar altimeters. Scatterometers measure the amount of reflected microwave energy, or backscatter, from the Earth's surface. Primary, scatterometers were designed to obtain information of the backscatter signal on wind speed and direction over
ocean surfaces (Elachi and Zyl 2006, Wentz et al. 2017), but their applications have been extended over soil moisture estimation as well (Batlivala et al. 1976, Oh et al. 1992, Wagner et al. 1999, Scipal et al. 2002). Examples of scatterometer sensors are NSCAT (NASA Scatterometer), QuickSCAT, SCATSAT-1, Oceansat-2, ISS-RapidScat, ERS-1/2 scatterometer, and ASCAT. ERS and ASCAT scatterometers used the C-band microwave frequency. Algorithms have been developed in order to enhance the retrieval of soil moisture using the latter instruments (Wagner et al. 1999, Bartalis et al. 2007, Naeimi et al. 2013). Radar altimeters were mainly designed to make measurements of the sea surface topography, but they have been used for other applications such as land hydrology (Birkett 1998, Birkett et al. 2002, Da Silva et al. 2010). The backscattering coefficient produced by radar altimetry was used to estimate soil moisture (Fatras et al. 2012). Examples of radar altimetry sensor are TOPEX/POSEIDON and ENVISAT (Ridley et al. 1996, Papa et al. 2003, Legrésy et al. 2005).

### 3.2.7 Imaging radars

Imaging radar sensors produce images, as opposed to non-imaging radar sensors. Radar images are composed of pixels (picture element) representing the radar backscatter of an observed surface or object. Seasat, launched in 1978, was the first oceanographic satellite that carried imaging radar systems into orbit. Thereafter, other imaging radar satellite like Radarsat and many more followed. It was showed that SAR systems (AIRSAR, E-SAR, ERS-1, JERS-1 and SIR-C) can be used over land for soil moisture retrieval (Dubois et al. 1995). Their capacity to provide spatial and temporal variations of the soil moisture at high spatial resolution and at a global scale has triggered interest in using imaging radars for soil moisture monitoring (Srivastava et al. 2009, Saradjian et al. 2011, El Hajj et al. 2016, Baghdadi et al. 2002).

## 4 Use of Earth observations in land surface modelling

It is widely acknowledged by the scientific community that LSVs are key components of the Earth's water, vegetation and carbon cycle. Understanding their behavior and simulating their evolution is a challenging task that has significant implications on many topics including, vegetation and biomass monitoring, numerical weather prediction and climate change. The LSMs play an important role in improving our knowledge of land surface processes and their interactions with the other components of the climate system. Initially developed to provide boundary conditions to atmospheric models, LSMs can now be used to monitor and forecast land surface conditions (Balsamo et al. 2015, Balsamo et al. 2018, Schellekens et al. 2017). They are however prone to errors owing to inaccurate initialization, forcing errors, incorrect parameterizations, or inadequate model physics.

Another way to monitor LSVs is through the use of observations (in situ, satellite remote sensing). Satellite Earth observations (EOs) are particularly relevant for the monitoring of LSVs. However all key LSVs cannot be observed from space. For instance, L-band, C-band, X-band passive and active microwave remote sensing traditionally used to estimate soil moisture is only sensitive to the first millimeters or centimeters of the top soil layer while the variable of interest for many applications in hydro-meteorology is the root zone soil moisture that controls processes such as evapotranspiration.

The modelling of terrestrial variables can be improved through the integration of Earth observations. Satellite EOs are particularly relevant in this context as the current fleet of EOs missions holds an unprecedented potential to quantify LSVs and many satellite-derived products relevant to the hydrological and vegetation cycles are already available at high spatial resolutions. Integrating observations into models covers several aspects:

- the mapping of the model parameters used to characterize the representation of land properties within the model (e.g., soil properties, land cover),
- the use of observations for model validation and evolution and
- the dynamic integration of observations into models through data assimilation techniques.
This PhD work focuses on the latter.

EOs provide long-term data records which can complement LSMs. Satellite products are particularly relevant for the monitoring of LSVs. A number of satellite-derived products relevant to the hydrological (e.g., soil moisture, snow depth, snow cover, terrestrial water storage), vegetation (e.g., leaf area index, biomass), and energy (e.g., land surface temperature, albedo) cycles are readily available globally, at kilometric and hectometric scales (e.g. Lettenmaier et al. 2015, Balsamo et al. 2018). Combining EOs and LSMs through a land data assimilation system (LDAS) can lead to enhanced initial land surface conditions (e.g. Reichle et al. 2007, Lahoz and De Lannoy 2014, Kumar et al. 2018, Albergel et al. 2017, 2018, 2019, Balsamo et al. 2018). Through the initialization of land surface conditions in atmospheric models, this can benefit weather forecasts, including atmospheric variables such as air temperature, air humidity, and precipitation. It can also indirectly benefit agricultural and vegetation productivity prediction, streamflow prediction, warning systems for floods and droughts and the representation of the carbon cycle (Bamzai et al. 1999, Schlosser and Dirmeyer 2001, Bierkens and van Beek 2009, Koster et al. 2010, Bauer et al. 2015, Massari et al. 2018, Albergel et al. 2018, 2019, RodríguezFernández et al. 2019).

A LDAS can be defined as a framework where a LSM is driven by (or ingests) Earth observations in order to produce enhanced estimates of the LSVs. Amongst the current landonly LDAS activities, several are led by NASA (National Aeronautics and Space Administration) projects. Examples of such activities are the Global Land Data Assimilation System (GLDAS, Rodell et al. 2004), the North American Land Data Assimilation System (NLDAS, Xia et al. 2012a,b) and the National Climate Assessment-Land Data Assimilation System (NCA-LDAS, Kumar et al. 2018, 2019). The Famine Early Warning Systems Network (FEWS NET) Land Data Assimilation System (FLDAS, McNally et al. 2017) is run over western, eastern and southern Africa. Additional examples include the Carbon Cycle Data Assimilation System (CCDAS, Kaminski et al. 2002), ORCHIDAS (https://orchidas.lsce.ipsl.fr/, Peylin et al. 2016), the Coupled Land Vegetation LDAS (CLVLDAS, Sawada and Koike 2014, Sawada et al. 2015), the Data Assimilation System for Land Surface Models using CLM4.5 (Fox et al. 2018) and the SMAP (Soil Moisture Active Passive) level 4 system (Reichle et al. 2019). Finally, LDAS-Monde (Albergel et al. $\mathbf{2 0 1 7}, \mathbf{2 0 1 8}, \mathbf{2 0 1 9}$ ) was developed by the research department of Météo-France.

One popular LDAS data assimilation approach has been the simplified extended Kalman filter (SEKF). It was introduced at Météo-France by Mahfouf et al. (2009) and was initially
designed for assimilating screen level atmospheric observations (e.g. 2-meter air temperature and humidity) to correct soil moisture estimates in the context of numerical weather prediction (NWP). Although the SEKF approach has provided good results, it suffers from several limitations and has been in competition with more flexible approaches, such as the ensemble Kalman filter (EnKF) (Reichle et al. 2002, Fairbairn et al. 2015, Kumar et al. 2018, 2020, Blyverket et al. 2019, among others) and particle filters (e.g. Pan et al. 2008, Plaza et al. 2012, Zhang et al. 2017, Berg et al. 2019).

Finally, assimilated EOs generally consist of satellite retrievals of surface soil moisture (Reichle et al. 2007, de Rosnay et al. 2013, Lievens et al. 2015, de Lannoy et al. 2013, Pinnington et al. 2018), snow depth (De Lannoy et al. 2012, Kumar et al. 2014, 2015) and snow cover (Fletcher et al. 2012, Zhang et al. 2014), vegetation (Barbu et al. 2011, 2014, Fairbairn et al. 2017, Leroux et al. 2018), as well as terrestrial water storage (Tangdamrongsub et al. 2015). Few studies involve the use of multiple EOs (Kumar et al. 2018, Albergel et al. 2020) or link the assimilated observations directly to several model variables (i.e. control variables).

At Météo-France, the Interactions between Soil, Biosphere, Atmosphere (ISBA) model (Noilhan and Planton 1989) was developed by the National Center of Meteorological Research (CNRM). The ISBA model has gradually evolved and is now a LSM within the SURFEX (Surface Externalisée, in French) surface modelling platform of Météo-France (Masson et al. 2013, and https://www.umr-cnrm.fr/surfex/, last access in September 2020). SURFEX is made of different physical models for urban surfaces, water bodies, ocean and land surface monitoring (see Figure II. 2 in chapter II).

In SURFEX, each model grid box is represented by four surface types: sea or ocean, water bodies (e.g. lakes), urban areas and "nature" (i.e. the soil-plant system). Each surface type is modelled with a specific surface model and the total flux of the grid box results from the addition of the individual fluxes weighted by their respective fraction. SURFEX main components can be summarized as follows:

- ISBA is the model for the "nature" tile,
- the model for the urban tile is TEB (Town Energy Balance),
- Surface fluxes above the "sea and ocean" tile can be treated in a simple way or by using a more physically based model,
- Surface fluxes above the lake tile can be treated in a simple way or by using FLake,
- Emission and deposition of dust and aerosols are treated over land and oceans,
- Assimilation of near surface meteorological variables and remotely sensed variables can be performed using different data assimilation schemes.

The standard version of the ISBA LSM uses a parsimonious approach and a small number of variables represent the soil state and the soil-plant-atmosphere exchanges. Only two soil layers are considered for the characterization of the soil water budget. Mean vegetation and soil properties are represented in a grid cell. Mahfouf et al. (1995) integrated the ISBA scheme to the ARPEGE Météo-France weather forecast and climate model. This version of ISBA is part of the SURFEX platform together with more recent and complex versions. Several improvements were made to the first version of ISBA. Noilhan et Mahfouf (1996) added a representation of gravitational drainage and Habets (1999) implemented a sub-grid surface runoff. Besides that, snow representation was improved as
well (Douville et al. 1995) and a third soil layer for the root zone was included (Boone et al. 1999). Furthermore, a multi-layer version of ISBA called ISBA-diffusion was designed to represent water and heat diffusion more explicitly using one-dimensional Fourier and Darcy laws throughout the soil (Decharme et al. 2011, Decharme et al. 2013). The fraction of frozen soil was also taken into consideration together with the vegetation insulation effect at the surface (Boone et al. 2000, Decharme et al. 2016). The ISBA parameters are usually defined for 12 generic land surface patches. They include nine plant functional types (needle leaf trees, evergreen broadleaf trees, deciduous broadleaf trees, C3 crops, C4 crops, C4 irrigated crops, herbaceous, tropical herbaceous, and wetlands) as well as bare soil, rocks, and permanent snow and ice surfaces. The ECOCLIMAP-II land cover database (Faroux et al. 2013) provides these parameters for each patch and each grid cell of the ISBA model.

There is also a $\mathrm{CO}_{2}$-responsive version of ISBA embedded within the SURFEX platform. In this configuration, ISBA simulates leaf-scale physiological processes and plant growth (Calvet et al. 1998, Calvet et al. 2004, Gibelin et al. 2006). The dynamic evolution of the vegetation biomass and LAI variables is driven by photosynthesis in response to atmospheric and climate conditions.

LDAS-Monde is the offline, global-scale and sequential-data-assimilation system dedicated to land surfaces developed by CNRM (Albergel et al. 2017, Albergel et al. 2020). LDAS-Monde permits the integration of satellite products into the ISBA LSM using a data assimilation scheme. The obtained reanalysis accounts for the synergies of the various upstream products. Several studies performed at CNRM (e.g. PhDs of Joaquin MuñozSabater in 2007, Clément Albergel in 2010, Marie Parrens in 2013, Postdoctoral fellowships of Christoph Rüdiger, Alina Barbu, Clara Draper, David Fairbairn, Emiliano Gelati, Delphine Leroux, Simon Munier, Bertrand Bonan and Yongjun Zheng) lead to the evolution of the CNRM offline LDAS from a point scale experiment in south-western France (e.g. Sabater et al. 2007) to a global capacity monitoring of the land surface conditions (e.g. Albergel et al. 2020).

The standard assimilation technique used in LDAS-Monde so far is the SEKF. A twostep sequential approach is used: a prior forecast step is followed by an analysis step. The prior forecast propagates the initial states to the next time step with the ISBA LSM and the analysis step then corrects this forecast by assimilating observations. The flow dependency (dynamic link) between the prognostic variables and the observations is ensured in the SEKF through the observation operator and its Jacobians, which propagate information from the observations to the analysis via finite difference computations (de Rosnay et al. 2013, Fairbairn et al. 2017). More recently, an Ensemble Kalman Filter (Fairbairn et al. 2015, Bonan et al. 2020) has been implemented. A Particle Filter approach is also currently under testing for snow data assimilation (Cluzet et al. 2020).

LDAS-Monde is embedded within the open-access SURFEX surface modelling platform and consists of the ISBA LSM coupled with the CTRIP river routing system and data assimilation schemes. Those routines assimilate satellite-based products of SSM and LAI to analyze and update soil moisture and LAI modelled by ISBA. The most recent SURFEX v8.1 implementation is used in this PhD work.

## 5 Objectives and work scope

The main objective of this PhD work entitled "Assimilation of satellite data for water resources monitoring in the Euro-Mediterranean area" is to assess to what extent the representation of land surface variables linked to the terrestrial water and carbon cycles in the ISBA LSM can be improved through the direct assimilation of ASCAT C-band backscatter $\left(\sigma^{0}\right)$ observations in ISBA.

The Land Surface Data Assimilation System (LDAS), LDAS-Monde, which has been developed at the National Centre of Meteorological Research (CNRM) is able to constrain the ISBA LSM using satellite derived observations. Many studies (Barbu et al. 2014, Farbairn et al. 2017, Albergel et al. 2017, 2018a,b, 2020, Leroux et al. 2018, Tall et al. 2019, Bonan et al. 2020, Mucia et al. 2020) have extensively applied the assimilation of either Leaf Area Index (LAI) or surface soil moisture (SSM) observations or both in order to monitor the terrestrial water and carbon fluxes using the LDAS-Monde. To the best of my knowledge (at least at the writing of this thesis report), the LDAS-Monde is now the only system able to sequentially assimilate vegetation products such as LAI to analyze both vegetation and root zone soil moisture. LDAS-Monde is also able to assimilate satellitederived SSM observations together with LAI.

The SSM used in the LDAS-Monde assimilation process is estimated from radar backscatter $\left(\sigma^{0}\right)$ observations from the ASCAT scatterometer instrument on board the Metop $\mathrm{A}, \mathrm{B}$, and C satellites. As $\sigma^{0}$ is indirectly related to soil moisture, retrieval methods making use of, for example, change-detection approaches (Wagner et al. 1999, 2013) are usually required to transform $\sigma^{0}$ into soil moisture values that can be assimilated in a LSM. This approach is efficient in eliminating soil roughness effects. Seasonal vegetation phenology effects are accounted for to some extent, but inter-annual variability in vegetation effects is not represented. As a result, a complex seasonal bias correction has to be performed before assimilating SSM in a LSM and the assimilation is not completely efficient during extreme events affecting vegetation such as droughts. Since $\sigma^{0}$ contains information on both SSM and vegetation variables, the LDAS can potentially directly use this information to better analyze soil moisture together with vegetation biomass.

Despite the proven record of assimilating retrieved soil moisture from point scale to regional and continental scale (e.g. Albergel et al. 2010, Draper et al. 2012, Matgen et al. 2012, de Rosnay et al. 2013, Barbu et al. 2014, Wanders et al. 2014, Ridler et al. 2014, Farbairn et al. 2017, Albergel et al. 2017, 2018a,b, 2020, Leroux et al. 2018, Tall et al. 2019, Bonan et al. 2020, Mucia et al. 2020, Kumar et al. 2018), there is an increasing tendency towards the direct assimilation of direct observations of level 1 products such as $\sigma^{0}$ observations (De Lannoy et al. 2013, Han et al. 2014, Lievens et al. 2015, 2017a). Retrieval methods usually make use of land surface parameters and auxiliary information, such as vegetation density indices and soil texture, possibly proving inconsistencies with specific model simulations. The latter also include these parameters but potentially from different sources. Also, if retrievals and model simulations rely on similar types of auxiliary information, their errors may be cross-correlated, potentially degrading the system performance (De Lannoy and Reichle 2016). The direct assimilation of $\sigma^{0}$ observations requires that the LSM be coupled to a radiative transfer model that serves as a forward operator for predicting $\sigma^{0}$. It has the advantage of allowing for consistent parameters and
auxiliary inputs between the model simulations and the radiative transfer model, avoiding cross-correlated errors. However, the used radiative transfer model has to be sufficiently accurate (Aires et al. 2005).

The development of a forward operator for $\sigma^{0}$ from active microwave instruments in the ISBA LSM is at the core of this PhD work, using a pre-existing radiative transfer model. It will allow vegetation effects to be accounted for in the signal using the vegetation information content of $\sigma^{0}$.

This PhD project is part of the HyMex programme (www.hymex.org) which studies the hydrological cycle of the Euro-Mediterranean area. HyMex aims at better identifying and describing the interactions between continental hydrology, atmosphere and the Mediterranean sea with the objective of improving the understanding and modelling of the water cycle in the Mediterranean.

In order to carry out this doctoral project, the following procedures were established and followed.

- Firstly, the task of designing or creating an observation operator capable of representing $\sigma^{0}$ from the variables simulated by ISBA on a global scale was implemented. The ISBA LSM products such as LAI and or SSM were linked to a set of mathematical equations (model) in order to get the $\sigma^{0}$ model output to be used for the assimilation processes.
- Secondly, a comparison of the simulated ISBA $\sigma^{0}$ output values with those observed from ASCAT sensors, and the quantification of the influence of various factors such as land cover, vegetation seasonal cycle, soil moisture and freezing conditions, on the $\sigma^{0}$ signal was carried out.
- Thirdly, the $\sigma^{0}$ observations were directly assimilated in ISBA and the impact of the assimilation on vegetation and on the various variables of the terrestrial water cycle was analyzed.
- Lastly, a comparative study of the assimilation of either SSM and LAI or $\sigma^{0}$ in ISBA LSM was carried out in order to evaluate the capability of the direct assimilation of $\sigma^{0}$ to improve the representation of LSVs linked to the terrestrial water and carbon cycles.

Chapter II describes the data and methods used in this work. Chapter III presents the implementation of a semi-empirical description of C-band $\sigma^{0}$ over the Euro-Mediterranean area, together with a detailed analysis of results over southwestern France (Shamambo et al. 2019). Results from the direct assimilation of $\sigma^{0}$ observations in ISBA over southwestern France are presented in Chapter IV. Microwave vegetation optical depth (VOD) at C-band is interpreted in Chapter V. Conclusions and prospects are given in Chapters VI and VII.

## CHAPTER II - Methodology

This chapter serves as a descriptive section of all the different components used in the methodology approach to carry out this thesis work. The organization of each section is as follows. The first part consists of outlining all the satellite observations used. Secondly, details of the LDAS Monde scheme with several components involved (ISBA LSM, atmospheric forcing and SEKF method) are tackled. The third part of this section gives details about the water cloud model (WCM) and how it is implemented as an observation operator. Finally, the calibration methods Shuffled Complex Evolution (SCE-UA) optimization technique used to calibrate the WCM model parameters is explained.

## 1 Observations

Various satellite observations have been used in order to realize the main objective of this thesis. Below is the description of all the satellite observations dataset products used.

### 1.1 ASCAT $\boldsymbol{\sigma}^{\circ}$ observations

Soil moisture cannot be directly observed from space. Indirect estimations of the surface and root-zone soil moisture states can be obtained using thermal infrared observations through the impact of soil moisture on the surface energy budget. In the visible light spectrum, soil color can be used to some extent to characterize surface soil moisture (SSM). A less indirect retrieval of SSM can be made through changes in dielectric permittivity properties of the soil in the microwave domain. Dielectric properties of soils are mainly driven by soil moisture. Other factors such as water salinity and temperature can also affect this quantity. At low microwave frequencies (e.g., C-band, L-band), the sensed signal is not affected much by atmospheric variables such as cloud coverage, and vegetation is generally not completely opaque. This means that SSM can be estimated, at least to some extent, in all conditions (day or night, clear or cloudy sky, bare or vegetated soil).

Two main categories of microwave sensors can be operated on satellites: radars and radiometers. The former are active sensors measuring backscatter from an illuminated target. The latter measure the natural emission of the Earth surface (expressed in terms of brightness temperature) together with a reflected component from the atmosphere and the space. Examples of currently operating L-band passive microwave sensors used to estimate SSM from space are SMOS and SMAP. Active sensors consist of either real aperture radars or synthetic aperture radars (SARs). Enhanced spatial resolutions can be obtained from the latter. For example, Sentinel-1 operates at C-band with backscatter data at spatial resolutions ranging from $20 \times 20 \mathrm{~m}^{2}$ to $80 \times 80 \mathrm{~m}^{2}$.

The Advanced Scatterometer (ASCAT) is a real-aperture C-band radar instrument which is on board the European Space Agency's (ESA) European Organization for the Exploitation of Meteorological Satellites (EUMETSAT) meteorological operational satellite (MetOp) series. While spatial resolution is about 6 orders of magnitude less precise than Sentinel-1, the same place can be observed at various incidence angles. Another advantage of ASCAT data is that observations are made at a global scale since 2006. After the launch of MetOp-C, daily ASCAT observations have been available in many places. Sentinel-1 observations are more recent and are available every 6 days at best over Europe.

The first MetOp named MetOp-A was launched in 2006 and in 2012, MetOp-B was also put in orbit. Recently, MetOp-C was also launched on 7 November 2018 from French Guiana. The ASCAT sensors replaced its predecessors ESA's scatterometer (ESCAT) on board European Remote Sensing (ERS-1 and ERS-2) satellites which were lauched in July 1991 and April 1995 respectively by ESA (Attema 1991; Long et al. 2001; Frison et al., 2016). ASCAT, like its predecessors (ERS-1 and ERS-2) operates in C-band with a VV polarisation. It must be noticed that the successor of ASCAT on MetOp-SG will include cross-polarization and horizontal copolarization (Stoffelen et al. 2017).

The main motivation of using this instrument in meteorological applications is the estimation of wind speed and wind direction across ocean surfaces. However, its applications have been extended over monitoring land processes on a regional or global scale as demonstrated by previous studies (Naeimi 2009; Frison et al., 2016, Bartalis et al., 2007, Shamambo et al., 2019; Vreugdenhil et al., 2016; Vreugdenhil et al., 2017; Schroeder et al., 2016; Lievens et al., 2017a). The EUMETSAT Hydrology Satellite Application Facility (HSAF) produces soil moisture products from ASCAT.

ASCAT instruments have configurations similar to ESCAT. The similarity between ASCAT and ESCAT is that the two scatterometers are based on the use of a fan-beam scatterometer created with three antennas illuminating the same swath: the fore (azimuth angle of $45^{\circ}$ ), midbeam (azimuth angle of $90^{\circ}$ ), and aftbeam (with azimuth angle of $135^{\circ}$ ) antennas (Frison et al., 2016; Marzano et., 2006; Migliaccio 2002; Gelsthorpe et al., 2000; Bartalis 2009). Below are the main ways in which ASCAT includes numerous improvements when compared to its predecessors:

- ASCAT instruments have increased coverage containing two 550 km swaths: one on each side of the satellite track direction (see Figure II.1). Each swath comprises of observations taken sequentially from the three antennae (fore-antenna, mid-antenna and aft-antenna).
- ASCAT's double swath configuration has improved spatial resolution and coverage, and this allows achieving near global coverage in a period of 5 days. ASCAT has 50 km spatial resolutions over $25 \times 25 \mathrm{~km}^{2}$ grid along and across both swaths. Moreover, a higher spatial resolution product is also generated using a $12.5 \times 12.5$ $\mathrm{km}^{2}$ grid.
- ASCAT instruments sigma-naught observations are made at 21 locations (called nodes) on either side of the satellite's track as compared to ERS with 19.
- ASCAT is a free-standing instrument and does not share a complex radar system with others like it was the case for the ERS scatterometer which were built to be part of Active Microwave Instrument consisting also of synthetic aperture radar (SAR). This permits no operation time being shared and hence better system robustness and continuous data acquisition.
- ASCAT instruments have higher incidence angle range leading to improved performance of the wind retrieval algorithm.
- ASCAT instruments have higher stability and reliability due to improved instrument design and radiometric performances.

ASCAT instruments are designed to measure the radar backscatter signal from the surface of the Earth at a frequency of 5.255 GHz and wavelength of 5.7 cm using a very good radiometric accuracy and stability. These radar backscatter signal are represented in terms of the Normalized Radar Cross-Section (NRCS) also referred to as sigma-naught ( $\sigma^{\circ}$ ) (Anderson et al., 2011). The NRCS are representative of the ratio of the received
backscatter coefficient energy to that of an isotropic scatterer as given by the radar equation which is well described in Bartalis (2009) and Naeimi (2009). The backscatter measurements are mostly given in units of $\mathrm{m}^{2} \mathrm{~m}^{-2}$ or decibels ( dB ). They are dependent on both the azimuth and incidence $(\theta)$ angles under which the object being observed is illuminated.

Table II. 1 - The main characteristics of the ASCAT scatterometer

|  | ASCAT |
| :--- | :--- |
| Frequency | 5.255 GHz (C-band) |
| Polarisation | VV |
| Incidence angle | $25^{\circ}-53.5^{\circ}$ (mid) <br> $33.7^{\circ}-64.5^{\circ}$ (fore/aft) |
| Azimuth angles | $45^{\circ}, 90^{\circ}$ and $135^{\circ}$ <br> (fore, mid-, aft beams respectively) |
| Wavelength | 5.70 cm |
| Radiometric stability | 0.46 dB |
| Repeat cycle | 29 days (412 orbits) |
| Swath Width (at nadir) | $2 \times 550$ km |
| Swath Stand-off | 336 km to the right/left of the sub-satellite track |
| Measurement nodes | 21 nodes for each 550km swath |
| Spatial resolution | 25 km (research mode) <br> 50 km (nominal mode) |
| Sampling $\quad$ Interval/Orbit <br> Spacing | Grid |
| Orbit | 2.5 km and 25 km |

The ASCAT instruments use incidence angles ranging from $25^{\circ}$ to $53^{\circ}$ for the midbeam and from $34^{\circ}$ to $65^{\circ}$ for the fore- and aft- breams and azimuth angles as elaborated in Table II.1. They fly in sun-synchronous orbits with a repeat cycle of 421 orbits equivalent to 29 days (Figa-Saldaña et al., 2002; Klaes et al., 2007; Wagner et al., 2013; Bartalis 2009, Naeimi et al., 2009). Rostan (2000) and Wilson et al. (2005) show that ASCAT instruments operate in mainly two modes: a measurement mode and a calibration mode. A chirp (linear frequency modulation) is used in the measurement mode. The echoes received from the transmitted chirp are de-chirped and Fourier-transformed so that the different ranges of signals are fit to different frequencies. For each chirp rate, a noise measurement and an internal calibration measurement are also made in addition to the ground echo. During the calibration mode, ASCAT sensors are put in relation with three transponders on
the ground that are located in Turkey in order to supply accurate and stable known point target cross sections (Anderson et al., 2009). The transponder transmits a time delayed signal (i.e. at $t_{i+1}$ ) different from inital $\left(t_{i}\right)$ when it receives a pulse during a pulse repetition cycle. Each calibration mode contains two antennas, one that is being measured by the transponder when it receives the time delayed pulse produced by the transponder and the other that is sending out a new pulse-repetition interval (EUMETSAT 2016; EUMETSAT 2017; Anderson et al., 2009; Bartalis 2009 et Naeimi 2009). There is a good amount of data that is reduced when pre-processing the echo and noise measurements on ASCAT sensor. This is necessary to remove pertubations on the signal being calculated by the sensors and enhance the production quality of the ASCAT dataset.

The ASCAT $\sigma^{\circ}$ data used in this study was obtained from the Vienna University of Technology (TUWien). Since ASCAT $\sigma^{\circ}$ measurements are acquired across a vast range of incidence angles, the dataset had undergone an interpolation process in order for the incidence angles to be fixed at $40^{\circ}$. A second-order polynomial developed by Wagner et al. (1999) was applied to the dataset for the interpolation process. The ASCAT $\sigma^{\circ}$ observations are available at $25 \mathrm{~km} \times 25 \mathrm{~km}$ or $50 \mathrm{~km} \times 50 \mathrm{~km}$ resolution as described in Table II.1, and for this study, $25 \mathrm{~km} \times 25 \mathrm{~km}$ spatial resolutions dataset was employed. This dataset is sampled on a discrete global grid of $12.5 \mathrm{~km} \times 12.5 \mathrm{~km}$. In order to fit the ASCAT $\sigma^{\circ}$ dataset to the $0.25^{\circ} \mathrm{x} 0.25^{\circ}$ grid that is used by the ISBA model, the data were interpolated to the model grid points. The ASCAT $\sigma^{\circ}$ used was also masked in order to remove the impact of frozen conditions and complex topography on the results.


Figure II. 1 - ASCAT Swath Geometry for Metop A (adapted from Bartalis 2009).

The Copernicus Global Land Service (CGLS) is the European service system providing information for land surface monitoring of bio-geophysical variables at a global scale. Under the CGLS, data is collected by sources such as Earth observation satellites or in situ sensors. Fraction of Absorbed Photosynthetically Active Radiation by vegetation (FAPAR), land cover, Soil Water Index (SWI), Surface Soil Moisture (SSM), Vegetation Condition Index (VCI), Vegetation Productivity Index (VPI), Fraction of vegetation Cover (FCOVER) and the true Leaf Area Index (LAI) are among the numerous products of the CGLS portfolio. The different products of the CGLS program are essential for monitoring dynamics of vegetation characteristics. The true LAI is defined as one half of the total green leaf area per unit horizontal ground surface area (Welles 1990; Chen et al. 1992) and it is part of the essential climate variables (ECVs) (GCOS-200, 2016). It is representative of the plant canopy structure and also very useful for considering canopy function since it is illustrative of the leaf surface where most of the biosphere-atmosphere processes of energy and mass happen (Welles 1990; McWilliam et al. 1993). Since LAI is a ratio of leaf area to surface area, it is a dimensionless quantity, mostly expressed as $\mathrm{m}^{2} / \mathrm{m}^{2}$. LAI is a key factor of photosynthesis primary production, evapotranspiration and the energy balance of the surface (Asner et al. 2003; Fuster et al. 2020; Sellers et al. 1997; Moran et al. 1995; Norman et al. 1995; Anderson et al. 2005; Doraiswamy et al. 2004).

LAI can be estimated from ground measurements (Breda 2003; Gower et al. 1999; Asner et al. 2003; lio et al. 2014) and earth observations (Xiao et al. 2013; Yang et al. 2006; Baret et al. 2007; Knyaikhin et al. 1998a; Knyaikhin et al. 1998b; Weiss et al. 2007). Remotely-sensed estimates of true LAI provide better spatial and temporal resolutions as compared to ground measurements which are costly and time consuming. In this study, GEOV2 LAI product that is produced by CGLS (http://land.copernicus.eu/global/, last seen 8 June 2020) is employed. This LAI product was interpolated by an arithmetic average to $0.25^{\circ}$ model grid points as in Barbu et al. (2014) and Albergel et al. (2017). It is derived from SPOT-VGT and PROBA-V sensors using a neutral network calibration which combines MODIS-15 (Myneni et al. 2002) and CYCLOPES (Baret et al. 2007) products in order to give the best estimates of CGLS LAI product. This true LAI product is available from 1999 to present and its retrieval approach is well detailed in Baret et al. (2013). Validation studies made by Camacho et al. (2013) demonstrated that the CGLS LAI is a reliable product and hence its usage has been extensively conducted in the ISBA LSM for several analyses i.e. data assimilation and other purposes (Albergel et al. 2017, 2018; Barbu et al. 2014; Leroux et al. 2018; Munier et al. 2018).

### 1.3 VOD

To enhance the understanding and estimation of vegetation which plays a vital role in linking water, energy and carbon cycle, numerous vegetation variables have been developed from remotely-sensed observations. Vegetation variables such as LAI (described above), Enhanced Vegetation Index (EVI), Vegetation Water Content (VWC), fraction of absorbed photosynthetically active radiation (FAPAR), Vegetation Index, solar induced fluorescence
(SIF) are usually calculated from optical and microwave observations frequency bands using several retrieval algorithms (Sun et al. 2018; Zheng et al. 2009; Myneni et al. 2010; Tang et al. 2020; Tucker et al. 2005; Kumar and Mutanga 2017; Myneni et al. 2002; Ceccato et al. 2002, Joiner et al. 2019). Many studies have demonstrated that different vegetation indices such as LAI and NDVI can be used to estimate green biomass of vegetation canopy. These indices are mostly retrieved from optical sensors.

However, a meaningful caveat about using optical sensors is that cloud cover affects the acquisition of data, hence limiting the coverage to only days without cloud cover. On the other hand, microwave measurements allow collecting dataset in all-weather conditions.

Since the 1990s, diverse studies have shown the importance of retrieving vegetation optical depth (VOD), which is a vegetation parameter that can be retrieved in the microwave region. The VOD is directly related to the dielectric properties and water content of the vegetation. Hence, VOD can be used as a proxy of vegetation canopy biomass and water content (Ulaby et al. 1982; Jones et al. 2013; Jones et al. 2014; Meesters et al. 2005). Since VOD is related to biomass, it can be used as an alternative to optical-based vegetation indices like NDVI, EVI and LAI (Jones et al. 2011). Numerous studies (Zribi et al. 2011; Kim et al. 2011; Momen et al. 2017) have demonstrated that VOD correlates to LAI to some exent. De Jeu (2003) illustrated that NDVI and VOD products are similar and mainly differ in physical nature of the actual radiation signals and how each parameter is retrieved. VOD retrievals from different microwave frequencies such as $\mathrm{C}-$, X -, K - and L- bands can be used to: improve the representation of GPP and evapo-transpiration via assimilation of VOD (Kumar et al. 2020), evaluate dryland vegetation dynamics (Andela et al., 2013), examine vegetation seasonality (Vreugdenhil et al. 2017; Guan et al. 2013, Guan et al. 2014), characterize extreme events such as droughts (Liu et al. 2015).

Here is an outline of some of the different microwave sensors that are employed to estimate VOD products: L-band soil moisture and ocean salinity (SMOS) mission (Fernandez-Moran et al, 2017), L-band NASA Soil Moisture Active Passive (SMAP) (Konings et al, 2017), X-band Advanced Microwave Scanning Radiometer for EOS (AMSR-E) (Lanka et al., 2017; Du et al, 2017), Ku-band Special Sensor Microwave/Imager (SSM-I) (Liang et al.,2019; Moesinger et al 2020; Owe et al, 2008) and C-band ASCAT radar backscatter (Vreugdenhil et al. 2016, Vreugdenhil et al. 2017).

In this study, we used VOD from ASCAT (ASCAT VOD) obtained from ASCAT $\sigma^{\circ}$ using the WCM in order to assess vegetation dynamics. This VOD product was provided by the Vienna University of Technology (TU-Wien, Austria). Vreugdenhil et al. (2017) demonstrated that the ASCAT VOD can capture inter-annual variability in vegetation and hence be used to enhance the understanding and monitoring of vegetation dynamics.

A description of the ISBA model is given together with an outline of the other versions of the ISBA model that are also incorporated in the SURFEX modeling platform.

### 2.1 SURFEX modeling platform and the different configurations of the ISBA model

As explained in section 4 of Chapter I, the Interactions between Soil Biosphere Atmosphere (ISBA) LSM is part of the SURFEX modelling platform of Meteo-France. ISBA is the model used to represent the nature surface types in the SURFEX modelling platform. There are four surface types (nature, sea and oceans, inland water surfaces (lakes and rivers) and town) in the SURFEX modelling platform (Figure II.2) (Masson et al. 2013). Each of these surface types is represented by an independent model. The Flake integral model has been integrated in SURFEX to represent inland water surfaces (lakes, rivers) (Mironov et al., 2008; Mironov et al., 2010). On the other hand, town energy balance (TEB) (Masson, 2000; Lemonsu et al., 2004) is the model that is used for urban parameterizations. Over sea and ocean surfaces, different bulk formulas such as Charnock's formula (Charnock 1955) and Louis's formula (Louis 1979) are computed for the estimation of fluxes and also the iterative Exchange Coefficients from Unified Multicampaigns Estimates (ECUME) (Belamari 2005; Belamari and Pirani, 2007) is used. The physical parameters and fractions of the different surfaces in the SURFEX platform are given based on ECOCLIMAP (Masson et al., 2003). Aspects related to the use of ECOCLIMAP in ISBA model are detailed in section 2.3.2. The SURFEX modeling platform can be run either in an 'online' mode or 'offline' mode. The 'online' mode is the version that is coupled with an atmospheric model as elaborated by Sarrat et al. (2009). On the other hand, the 'offline' mode is not connected to the atmosphere and must be forced by atmospheric forcings. This study uses the 'offline' mode of the SURFEX platform where the different atmospheric forcings are applied (see section 2.3.1 that describes the atmospheric forcings used in this work). During the 'offline' configuration of the SURFEX platform, the ISBA model can be used to simulate heat and water transfer in its different modules that include the soil, vegetation, snow and surface hydrology.

The ISBA LSM has undergone a lot of new configurations from its first version that was designed by Noilhan and Planton (1989). All the different configurations of the ISBA model are integrated in the SURFEX modeling platform. The first version of ISBA model is referred to as ISBA-Standard which was established based on first generation model known as 'bucket model' as detailed in section 2 of Chapter I.

In the standard ISBA model, the soil is represented by two layers. The first layer is comprised of an upper layer of the surface. This first layer is about 1 cm thick and is used to simulate the surface soil moisture and temperature. The second layer is thicker than the first one and includes the root zone. The thickness of the second layer is dependent on the vegetation type and on the nature of the soil. The standard ISBA option represents the vegetation as a single layer with 8 parameters used to classify it (Noilhan and Planton, 1989; Noilhan and Mahfouf, 1996). The root depth (d2), stomatal resistance (RSmin) and the contribution of the vegetation to the coefficient of thermal inertia of the surface $(\mathrm{Cv})$ are the three parameters that are constant over time. The other five parameters (proportion of
vegetation (veg), LAI, length of roughness (z0), albedo ( $\alpha$ ) and emissivity ( $\varepsilon$ )) vary and depend mostly on the seasonal cycle. In order to calculate the evapotranspiration via the stomata resistance, the simple Jarvis (1976) method is used in this standard ISBA model. This method is established on four components accounting for water vapour deficit, air temperature dependence of the surface resistance, the water stress and photosynthetically active radiations (Masson et al. 2013). The initial ISBA standard model with 2-layer representing the soil water content profile did not easily differentiate the root zone and subroot zone soil water schemes. In order to account for this problem, Boone et al. (1999) included a third layer which resulted into an extensive improvement in modeling results using the ISBA standard model. A further development of the ISBA model lead to the establishment of a multi-layer ISBA version (the ISBA-DF option is described in more detail in Chapter I, section 4) with 14 layers going as deep as 12 m . The introduction of ISBA-DF made it possible to take into account the deeper vertical variability of the profile of water content (liquid and solid) and temperature for the different involved soil layers. The version of the ISBA model able to represent photosynthesis and plant growth is called "NIT" in the SURFEX modelling platform. The section that follows focuses on this newer version of the ISBA model, comprising the DF and NIT options.


Figure II. 2 - Schematic representation of the SURFEX modeling platform (adapted from Masson et al. 2013).

### 2.2 Main characteristics of the ISBA model

Since the simulations conducted in this thesis project were done within the framework of the ISBA model interactive vegetation option initially developed by Calvet et al. (1998), it is necessary to provide some details on the architecture of the model and the physical processes that it uses to simulate the different biophysical variables (Figure II.3). The interactive vegetation version of ISBA is primarily designed to simulate LAI and leaf stomatal conductance following soil properties, climate and atmospheric carbon dioxide concentration. The notation A-gs making the newer version of ISBA to be called "ISBA-Ags" implies, for letter A the net $\mathrm{CO}_{2}$ assimilation and for gs the leaf stomatal conductance. LAI and leaf stomatal conductance are the two major vegetation elements that constrain the water and $\mathrm{CO}_{2}$ interchange between the atmosphere and vegetation in LSMs (Gibelin et al., 2006).

In order to describe the photosynthesis phenomenon in ISBA, a model developed by Jacobs et al. (1996) is used. This model is based on the approach by Goudriaan et al. (1985) that was then modified by Jacobs (1994) and Jacobs et al. (1996). The very purpose of this model is to estimate the rate of net uptake of $\mathrm{CO}_{2}$ by vegetation depending on numerous limiting environmental factors such as: solar radiation, atmospheric $\mathrm{CO}_{2}$ concentration, leaf temperature, air saturation deficit in water vapor. The parameterization approach derived from a set of equations commonly used in other surface models such as those of Farquhar et al. (1980) when catering for C3 plants and Collatz et al. (1992) for C4 plants are also employed in the ISBA model allowing for the possibility of taking into account these vegetation types. The mesophyll conductance ( $\mathrm{g}_{\mathrm{m}}$ ) is representative of the $\mathrm{CO}_{2}$ transfer conductance within plant leaves during leaf photosynthesis in ISBA.

The Jacobs model was updated by Calvet et al. (1998) in order to account for soil water stress effects. The internal concentration of $\mathrm{CO}_{2}$ at a given value of $\mathrm{g}_{\mathrm{m}}$ impacts photosynthetic capacity and is related to physiological processes such as plant response to soil water stress. The representation of the water stress is dependent on soil moisture in the root-zone. Vegetation can depict two sets of response to stress, for example whether herbaceous vegetation is being considered (Calvet, 2000) or forest vegetation (Calvet et al., 2004), plant might face either drought tolerance or drought avoidance depending on the evolution of water use efficiency under the underlining drought conditions.


Figure II. 3 - Summary of the "NIT" option of the ISBA model in SURFEX, able to simulate interactive LAI, herbaceous above-ground biomass, and drought-avoiding and -tolerant responses to soil water deficit. Net assimilation (An) at the canopy level is calculated, together with stomatal conductance (gs), gross primary production (GPP) and ecosystem respiration. Surface variables include atmospheric $\mathbf{C O}_{2}$ concentration, incoming solar radiation $\left(R_{G}\right)$, leaf surface temperature ( $T_{s}$ ), and leaf-to-air saturation deficit ( $D_{s}$ ). Plant specific model parameters include mesophyll conductance in optimal conditions ( $\mathrm{g}_{\mathrm{m}}$ ) at a temperature of $25^{\circ} \mathrm{C}$, maximum leaf-to-air saturation deficit ( $\mathrm{D}_{\text {max }}$ ), the ratio ( $\mathrm{f}_{0}$ ) of internal to external $\mathrm{CO}_{2}$ concentration (the $\mathrm{CO}_{2}$ compensation point in optimal conditions (no soil moisture stress and Ds $=0 \mathrm{~g} \mathrm{~kg}{ }^{-}$ ${ }^{1}$ ) being subtracted from both values). Specific Leaf Area (SLA) is the ratio of LAI to active biomass within green leaves. Leaf plasticity parameters (e and f) depending on vegetation type control the response of SLA to changes in leaf mass-based nitrogen concentration $\left(\mathrm{N}_{\mathrm{L}}\right)$. Note: another version of the model has to be activated in order to simulate carbon storage in the soil and in trees in addition to the herbaceous aboveground biomass.

In order to model LAI in ISBA, a simple vegetation growth model (Calvet and Soussana, 2001) which converts the net carbon assimilation of $\mathrm{CO}_{2}$ by the plant during photosynthesis into LAI is used (Figure II.4). A minimum LAI value is prescribed in the growth and mortality module in order to allow the plant to assimilate $\mathrm{CO}_{2}$ when conditions become favorable for the photosynthesis process. The minimum value set depends on the vegetation type being considered. For coniferous forest, it is set at $1 \mathrm{~m}^{2} \mathrm{~m}^{-2}$ and $0.3 \mathrm{~m}^{2} \mathrm{~m}^{-2}$
for other land cover types. It must be noticed that in ISBA, plant phenology is completely driven by photosynthesis. No growing degree-day parameterization based on air temperature is used. As a result, the simulated LAI is very flexible and LAI observations can easily be integrated into the model at any time. Another advantage is that the simulated LAI can rapidly respond to rainfalls through the root-zone soil moisture impact on photosynthesis. This is particularly useful in semi-arid areas where water is the main limiting factor of plant growth. The strong link between LAI and root-zone soil moisture in dry conditions can be used to analyze the ISBA root-zone soil moisture through the assimilation of LAI observations (see below the LDAS-Monde description).

The ECOCLIMAP system described in section 2.3 .2 is used to define the ISBA parameters using 12 land surfaces patches.


Figure II. 4 - Carbon allocation in the ISBA model for herbaceous above-ground green vegetation.

### 2.3 Atmospheric forcing and land use

In order for LSMs to be used for estimation of fluxes and surface states, they must be constrained by atmospheric forcing and parameter data. The ISBA model was forced by ERA-5 atmospheric meteorological data and for parameter data representation, ECOCLIMAP was used. Below are subsections detailing the usage of the atmospheric forcing and the land database employed in the ISBA LSM.

### 2.3.1 Atmospheric forcing dataset

The European Centre for Medium-Range Weather Forecasts (ECMWF) ERA5 gridded atmospheric re-analysis (Hersbach and Dee, 2016; Hersbach et al., 2020) is the atmospheric forcing that was used to drive the ISBA LSM. This product is available globally every hour at a $31 \mathrm{~km} \times 31 \mathrm{~km}$ horizontal spatial resolution (Dee 2020). The ERA5 atmospheric re-analysis comprises of surface atmospheric variables such as surface pressure, air temperature, incoming shortwave and longwave radiation values, precipitation, relative humidity and wind speed. In order to incorporate the ERA5 atmospheric re-analysis forcing within the ISBA LSM, the atmospheric forcing is interpolated to a $0.25^{\circ} \times 0.25^{\circ}$ grid using a bilinear interpolation (Albergel et al. 2018, Bonan et al. 2020).

### 2.3.2 A land use database: ECOCLIMAP

The physical parameters and fractions of a LSM are dependent on the numerous parameter values related to vegetation, soil and other surface conditions (Santanello et al., 2013). In this study, the ECOCLIMAP II (Faroux et al., 2013) is used to extract soil and vegetation types for each ISBA grid cell and patch fraction. ECOCLIMAP II land database is a new version of the ECOCLIMAP database (Masson et al., 2003) and is available for Europe and Africa. The ECOCLIMAP database is based on a $1 \mathrm{~km} \times 1 \mathrm{~km}$ resolution that was derived from the CORINE land cover dataset (CEC 1993) at 250 m resolution over Europe and in cases where the CORINE land cover was missing, the PELCOM dataset (Mucher 2001) was used. ECOCLIMAP II includes 273 vegetation ecosystems that are then regrouped into 12 land cover categories. For a given grid point, each of the 12 classes of the land cover represents a certain fraction of the grid. The 12 categories of the land cover include: three non-vegetated surface types (permanent snow, rock and bare soil) and nine vegetative land cover types (coniferous trees, deciduous broadleaf trees, evergreen broadleaf trees, C3 crops, C4 crops, temperate grasslands, tropical grasslands, wetlands, and irrigated crops).

## 3 LDAS-Monde

The LDAS-Monde tool is a sequential and global-scale land data assimilation system that operates in an offline mode. LDAS-Monde is implanted in the SURFEX surface modelling platform. It is made up of the ISBA land-surface model that is coupled to CTRIP river routing system and a data assimilation method. LDAS-Monde, to my knowledge (as of today at the writing of this PhD manuscript), is the only land data assimilation that is
capable of assimilating, in a sequential way, satellite products that describe the vegetation such as LAI together with SSM for the analysis of vegetation biomass and root-zone soil moisture. Surface soil moisture and leaf area index are the satellite products that have been routinely assimilated in order to analyze and update the LAI and the surface and root-zone soil moisture that are modelled by the ISBA LSM (Albergel et al. 2010; Barbu et al. 2011; Barbu et al. 2014; Fairbairn et al. 2015; Albergel et al. 2017, Bonan et al. 2020). As for this study, the direct assimilation of the ASCAT $\sigma^{\circ}$ observations is carried out to improve the representation of ISBA variables (LAI and soil moisture). All the experiments in this study were carried out in the latest version of the SURFEX platform (SURFEX v8.1). The data assimilation technique that is employed is called simplified extended Kalman filter (SEKF) which comprises of using fixed estimates of background error variances without any spatial covariances being considered at each start of each initial cycle (Mahfouf et al. 2009; Barbu et al. 2011, Barbu et al. 2014). This method is incorporated into the LDASMonde system and optimally combines ISBA outputs and satellite observations in order to provide an analysis. The analysis is representative of the corrective trajectory of the simulated soil moisture and LAI. LDAS-Monde system carries out the data assimilation procedure for each grid point independently with no covariance being treated. The LDASMonde is run with a 24 hour assimilation window with each 24 hour cycle consisting of two steps: a forecast step and an analysis step. The forecast step is where the trajectory of the state of the system is propagated from the initial time $t$ to $t+24$ hours using the ISBA model. As explained by Barbu et al. (2014) and Bonan et al. (2020), for each ISBA grid cell, the forecast of $\boldsymbol{x}$ denoted by $\boldsymbol{x}^{\mathrm{f}}(\mathrm{t}+24 \mathrm{~h})$, only relies on the analysis at time $\mathrm{t}, \boldsymbol{x}^{\mathrm{a}}(\mathrm{t})$. The non-linear ISBA parameterization procedure for each grid cell is represented by $M$ in Equation II.1.
$\boldsymbol{x}^{\mathrm{f}}(\mathrm{t}+24 h)=M\left(\boldsymbol{x}^{\mathrm{a}}(\mathrm{t})\right)$

The notation 'a', ' f ', and ' o ' are superscripts for analysis, forecast and observation, respectively. The term $\boldsymbol{x}$ is used to indicate the control vector that is computed at a given time characterizing the prognostic equations of the ISBA LSM. The term $y$ is use to designate the observations $\left(\boldsymbol{y}^{\mathrm{o}}\right)$ or the model equivalent of the observations $\left(\boldsymbol{y}^{\mathrm{f}}\right)$. Once the $\boldsymbol{x}$ model state variable has been propagated in time, a non-linear observation operator $\mathbf{H}$ is used to transform $\boldsymbol{x}$ to the model equivalent of the observations. In the Simplified Extended Kalman Filter (SEKF) technique I used, the model equivalent of the observations $\boldsymbol{y}^{f}=\mathbf{H}\left(\boldsymbol{x}^{\mathrm{f}}\right)$ is calculated and compared with the observations at the model grid-cell level. In the analysis step, the Kalman gain $\mathbf{K}$ is calculated using a Jacobian matrix ( $\mathbf{J}$ ) involving the product of $\mathbf{H}$ and $M$ :

$$
\begin{align*}
& \boldsymbol{x}^{\mathrm{a}}=\boldsymbol{x}^{\mathrm{f}}+\mathbf{K}\left(\boldsymbol{y}^{\mathrm{o}}-\mathbf{H}\left(\boldsymbol{x}^{\mathrm{f}}\right)\right)  \tag{II.2}\\
& \mathbf{K}=\mathbf{B J}^{\mathrm{T}}\left(\mathbf{J B} \mathbf{J}^{\mathrm{T}}+\mathbf{R}\right)^{-1} \tag{II.3}
\end{align*}
$$

$\mathbf{J}(\mathrm{t}+24 h)=\frac{\boldsymbol{\partial}\left(\mathbf{H}\left(M\left(x^{\mathrm{a}}(\mathrm{t})\right)\right)\right)}{\partial \boldsymbol{x}^{\mathrm{a}}(\mathrm{t})}$

Equation II. 3 demonstrates how the Kalman gain is computed. The $\mathbf{B}$ and $\mathbf{R}$ terms are representative of the error covariance matrices for the forecast and for the observations, respectively. The Jacobian matrix $\mathbf{J}$ and its transpose $\mathbf{J}^{\mathrm{T}}$ represent a linearized version of the observation operator that links the model states to the observation space. A finite differences method is used to numerically calculate each Jacobian element using perturbed model runs as elaborated by Equation II.4. and Figure II.5.

The control vector used comprises prognostic variables of the ISBA LSM for each considered grid cell. The first layer of the soil $(0-1 \mathrm{~cm})$ is driven by atmospheric forcing to a large extent as demonstrated by the studies of Draper et al. (2011) and Barbu et al. (2014). Surface soil moisture from layer 2 at depth of 1-4 cm, down to layer 7 ( $60-80 \mathrm{~cm}$ depth) and LAI are used as control vector variables. Eight control variables are used (Figure II.5): LAI, SSM, and soil moisture in the root-zone for six soil layers.

LDAS-Monde is able to jointly assimilate LAI and SSM observations. Alternatively, only LAI, or only SSM can be assimilated. A unique property of LDAS-Monde is that LAI observations can be used to analyze the root-zone soil moisture.

As explained by Barbu et al. (2014) and Bonan et al. (2020), LDAS-Monde is also able to manage vegetation patches in order to account for the sub-grid land cover variability. This capability was not used in this work.


Figure II. 5 - LDAS-Monde 24 hour assimilation cycle: forecast and analysis of 8 control variables using the SEKF (adapted from Tall et al. 2019).

## 4 Observation operator: the Water Cloud Model

Satellite instruments generally measure radiances. These observations can be converted to level 1 products such as brightness temperature or radar backscatter coefficient. More often than not, level 1 products are not directly representative of the geophysical variables that can be compared with model simulated variables. On the other hand, level 2 products such as LAI or SSM (derived from level one products) are closer to what can be simulated by a LSM. Possible shortcomings of assimilating level 2 products are that (1) the algorithms producing level 2 products use data also used in the LSM, (2) the sensitivity of the level 1 observations to various model variables is lost in level 2 products. This is why I tried to test the assimilation of ASCAT $\sigma^{\circ}$ data instead of assimilating the ASCAT-derived SSM product. It is expected that $\sigma^{\circ}$ data are sensitive to the model SSM simulations but also to LAI simulations.

In order to represent the level 1 satellite products in LMSs via data assimilation scheme, a modelled equivalent of the observations needs to be calculated to allow comparison of the two datasets. Such a model acts as an observation operator that links the model variables and the observations (Lorenc 1986; Pailleux 1990). In this study, the Water Cloud Model (WCM) developed by Attema et al. (1978) was used as a new observation operator in LDAS-Monde to convert ISBA variables into ASCAT $\sigma^{\circ}$ observations. The WCM is a simple computing-cost effective, semi-empirical approach with few parameters to be tuned. The following paragraphs give details about the water cloud model and how it is used (see also Shamambo et al. 2019).

A radiative transfer model can be used as a mechanism to calculate the propagation of radiation through a vegetation canopy (Fung et al., 1994; 2010; Liang et al., 2012). As mentioned before, this study uses the WCM which is based on a simplification of the radiative theory to simulate the total radar backscatter signal $\sigma^{0}$ as a function of soil moisture and vegetation variables. Despite the fact that there are several models that can be used to model radar backscatter signals using vegetation and/or soil surface parameters based on the radiative transfer algorithms (Van Oevelen and Hoekman 1999; Eom and Fung 1984; Ulaby 1990; Saatchi et al., 1994; Karam et al., 1992; Liang 2005; Baghdadi et al., 2016), the WCM model stands out as a more robust approach to build an observation operator because of its relative simplicity and low computing cost. The WCM uses few biophysical variables and only a few parameters need to be fitted before implementing it. The WCM can act as an inversion model to retrieve vegetation and soil moisture parameters (Clevers and Van Leeuwen 1996; Moran et al., 1998; Liu and Shi 2016; Paloscia et al., 2013; Joseph et al., 2010; Zribi et al., 2011; Gherboudj et al., 2011; Prevot et al., 1993; Le Toan et al., 1997). The model accounts for the incidence angle $\theta$ but in this work, $\sigma^{0}$ observations are interpolated at an incidence angle of $\theta=40^{\circ}$.

The WCM assumes that the vegetation canopy can be modelled as a collection of water droplets which are uniformly distributed within the vegetation canopy. The WCM assumption is based on the fact that the dielectric constant of vegetation canopy (which is a mixture of vegetative matter and water) is related to the dielectric constant of water (Ulaby et al., 1984; Ulaby et al., 1986). Generally, the radar backscattering from a vegetated soil surface comprises of: (i) scattering contribution from the vegetation ( $\sigma_{v e g}^{0}$ ), (ii) multiple
scattering contribution from vegetation and the soil ( $\sigma_{v e g+\text { soil }}^{0}$ ), and (iii) the scattering contribution from the soil $\left(\sigma_{\text {soil }}^{0}\right)$, attenuated twice by the vegetation layer $\left(t^{2}\right)$ :
$\sigma_{\text {total }}^{0}=\sigma_{\text {veg }}^{0}+\sigma_{\text {veg }+ \text { soil }}^{0}+t^{2} \sigma_{\text {soil }}^{0}$
However, in like-polarized radiation (i.e., VV polarization of the ASCAT dataset used in this work), the interaction of the incident radiation between the vegetation canopy and the underlying soil surface is not a dominating factor and thus can be ignored (Dobson and Ulaby 1986, Prévot et al. 1993b; Kumar et al. 2015).

After neglecting the second term in Eq. II.5, the modified equation becomes:
$\sigma_{\text {total }}^{0}=\sigma_{v e g}^{0}+t^{2} \sigma_{\text {soil }}^{0}$
with
$\sigma_{\text {veg }}^{0}=A V_{1} \cos \theta\left(1-t^{2}\right)$
$t=e^{-\frac{B V_{2}}{\cos \theta}}$
and
$\sigma_{\text {soil (dB) }}^{0}=10 \log _{10} \sigma_{\text {soil }}^{0}=C+D \times \mathrm{SSM}$

It must be noticed that the $B V_{2}$ term in Eq. II. 8 represents VOD:
$\mathrm{VOD}=B V_{2}$
where $V_{1}$ and $V_{2}$ are representative of vegetation descriptors.
A schematic representation of the WCM can be found in Figure 2b of Ulaby et al. (1984).
Several options can be used for representing $V_{1}$ and $V_{2}$. For example, the same vegetation variable can be used for both $V_{1}$ and $V_{2}$ (Ulaby et al. 1984; Lievens et al. 2017a; Zribi et al. 2011; Baghdadi et al. 2017). Alternatively, different variables can be designated to act as $V_{1}$ and $V_{2}$ (Prévot et al. 1993; Chauhan et al. 2017; Paris 1986; Kumar et al. 2012). Some studies (Attema and Ulaby 1978; Ulaby et al. 1984; Prévot et al. 1993; Champion 1996; Leeuwen et al. 1994) set $V_{1}$ as 1 for some specific conditions of
analysis. A variety of biophysical variables such as LAI, NDVI, VOD, vegetation water content, FAPAR, FCOVER, areal density of leaves, normalized plant water content, etc. can be used as vegetation descriptors in the WCM. There is no universal theoretical method to characterize the best group of vegetation descriptors, and thus, to retrieve the values of the $A$ and $B$ vegetation parameters (Prévot et al., 1993). The $A$ and $B$ parameters are dependent on the canopy type and radar configurations.

In this study, both configurations of the WCM (version 1 where $V_{1}=1$ and $V_{2}=\mathrm{LAI}$; and version 2 where $V_{1}=$ LAI and $V_{2}=$ LAI) were tested. The preliminary tests showed that that using version 1 with $V_{1}=1$ and $V_{2}=\mathrm{LAI}$, produced more accurate results. Hence throughout the experiments carried out for this PhD project, version 1 was employed.

Parameter $C$ is the value of the backscatter coefficient for a perfectly dry soil and is essentially controlled by surface roughness and incidence angle. Parameter $D$ refers to the radar sensitivity to variations in soil moisture, which is dependent on radar configurations. The two parameters ( $C$ and $D$ ) are bare soil parameters which are obtained by a linear model fitting as expressed in Eq. II.9, where $\sigma_{\text {soil }}^{0}$ is expressed in dB (Attema and Ulaby 1978, Hirosawa et al. 1978; Champion 1996 ; Bernard et al. 1982 ; Dobson and Ulaby 1986).

SSM is the volumetric soil moisture which, in this study, is representative of the first $1-4 \mathrm{~cm}$ layer of the soil moisture simulations by the ISBA LSM. In order to calculate the values of the $A, B, C$ and $D$ parameters related to the WCM in this study, the calibration process was done in linear scale. Hence the soil contribution described in Eq. II. 9 had to be converted from decibels using Eq. II. $\mathbf{1 1}$ in order to have all the equations expressed in the same units.

However, for the purposes of representing the simulated $\sigma^{\circ}$ from WCM with that from the ASCAT observations on the same time series graphs (see results in section 1.4 of Chapter III), the units were then reconverted to dB using Eq. II.12.

$$
\begin{align*}
& \sigma_{\text {soil }}^{0}=10^{\left(\sigma_{\text {soil }(d B)}^{0} / 10\right)}  \tag{II.11}\\
& \sigma_{\text {soil }(d B)}^{0}=10 \log _{10}\left(\sigma_{\text {soil }}^{0}\right) \tag{II.12}
\end{align*}
$$

The WCM model is a semi-empirical model so its parameters $A, B, C$ and $D$ are computed by calibrating the model against already available experimental datasets (Prévot et al. 1993; Xu et al. 1996; Bindlish and Barros 2001a, 2001b). Hence, the reliability of the estimated parameters depends upon the quality of the experimental data and the nature of the objective function used (Kumar et al. 2012; Steele-Dunne et al. 2017).

In this study, two calibration methods that are explained in the sections that follow were tested in order to calibrate the water cloud model parameters.

## 5 Model calibration

Advances in the development of scientific models (i.e., physical, conceptual and mathematical models) have been useful in enhancing the representation of complex systems. These models are often designed with a large number of parameters which are not directly and easily measurable. There must be ways to infer the unknown model parameters from using observation datasets which include information of model's state variables. In the science community, this is a major challenge because if model parameters cannot be efficiently and precisely calculated, the variables that are obtained from using such models are not so reliable. The performance of models depends on model structure, calibration conditions, observed data and optimization procedure (Sorooshian et al. 2008). Since the advent of scientific models, various methods have also been established in order to enhance the estimation of model parameters. The different optimization techniques that can be used to calibrate a model usually consist of finding a fit between the observed outputs and simulated outputs through the use of an objective function. The main objective of using optimization techniques is to find the best suitable values for the model parameters that maximize or minimize (depending on the need) the chosen objective function also referred to as a cost function. Several studies have demonstrated the use of different optimization methods in order to efficiently calibrate models for accurate representation of ecosystem processes. Kennedy and Eberhart (1995) developed the particle swarm optimization method that is used to optimize continuous nonlinear functions. The particle swarm optimization method was successfully tested by Bandara et al. (2015) when optimizing the parameters of soil properties within the Joint UK Land Environment Simulator (JULES) using soil moisture satellite observations from SMOS. Sawada (2019) used a combination of the Markov Chain Monte Carlo (MCMC) and machine learning methods to optimize parameter representation in the EcoHydro-SiB LSM. Other examples of optimization methods include: pattern search (Hooke and Jeeves, 1961), downhill simplex (Nelder and Mead 1965), adaptive random search (Masri et al. 1980; Brazil 1989), genetic algorithm (Holland 1975; Goldberg 1989), simulated annealing (Kirkpatrick et al. 1983) and multicriteria methods (Gupta et al. 1999).

In this study, two optimization methods (Non-Linear Least-Square Fitting (Newville et al., 2015) and Shuffled Complex Evolution method) were tested when calibrating the WCM model parameters within the ISBA LSM. Preliminary tests showed that the Shuffled Complex Evolution method was the most efficient.

The Shuffled Complex Evolution (SCE-UA) method is an optimization method that was initially designed by Duan et al. (1992, 1993) for the calibration of conceptual hydrological models. Since its creation, the SCE-UA algorithm was used in many scientific and engineering applications (more details of the use of the SCE-UA method are given in Naeini et al. (2019)). The performance of the SCE-UA depends on a small number of parameters that need to be defined by the user. In SCE-UA algorithm, the population is partitioned into sub-populations that are referred to as complexes. The SCE-UA method requires the use of the Competitive Complex Evolution (CCE) to evolve the complex at every iteration. When the processing of the CCE is finished, all the complexes are regrouped to create the main population. Then another segmentation and division to create new complexes, will shuffle the population and complexes. Hence the reason it is called Shuffled Complex Evolution, the UA is an abbreviation of the University of Arizona
because this method was developed there. In my article Shamambo et al. (2019) that is discussed in Chapter III, the lay-out of how the SCE-UA is used in this PhD is outlined.

When a model is carefully calibrated, it will accurately be able to model the different ecosystems it is representing. Hence, it is important to choose an optimization method that will provide consistent results with the phenomenon being represented by the model. Throughout this study, the SCE-UA method was retained for all calibration processes of the WCM because it leads to the estimation of better-constrained WCM parameters when compared to results obtained using other methods (not shown). It must be noticed that the choice of the cost function to be minimized is critical. In this study, the root mean square difference between observed and modelled ASCAT $\sigma^{0}$ was used together with a parameter penalty term, as described in Lievens et al. (2017a). See also Equations (9) and (10) in Shamambo et al. (2019).

It must be noticed that the WCM calibration is made at the model grid-cell scale. This means that if a change in land cover occurs over the same grid-cell, the model may no longer be valid. The stability of the calibration through time needs to be verified.

## CHAPTER III - Using satellite scatterometers to monitor land surface variables

Land surface variables influence the partitioning of carbon, water and energy fluxes of terrestrial ecosystems. These fluxes then affect the climate system. The interactions between the climate system and the terrestrial ecosystem are not easy to represent and involve a lot of processes that in many cases are not well represented. Variations in climate affect not only the environment but also the socio-economic aspects on all scales (Muradov and Veziroglu 2016). Enhancing ways of understanding the status of LSVs and identifying the key influencing factors is needed for monitoring land surface processes. The use of remote sensing has become cardinal for representing and understanding land surface processes. Recent advances in satellite missions with instruments which are sensitive to vegetation biomass and soil moisture have led to continued provision of Earth observation data. This is particularly true for all-weather active and passive microwave sensors. Among the active microwave sensors, scatterometers, which were initially designed for the purpose of acquiring information on wind speed and direction over the ocean surface have now seen their applications extended to monitoring land surface processes. The aim of this chapter is to assess to what extent land surface conditions can be characterized using C-band VV polarization backscatter observations from the ASCAT scatterometer (Wagner et al. 2013). Land surface conditions related to soil moisture and vegetation density are assessed over the whole Euro-Mediterranean area. Further analysis is made over southwestern France in order to investigate the impact of several additional factors related to land cover change, to crop type, and to geomorphology. For all areas of interest, the ISBA LSM is combined with the backscatter water cloud model (WCM). The SCE-UA optimization method is used to calibrate the WCM over the Euro-Mediterranean area. The capacity of using the WCM model to simulate ASCAT $\sigma^{\circ}$ at an incidence angle of $40^{\circ}$ and VV polarization is examined for different seasons and regions of interest. The robustness of the WCM calibration is assessed in more detail over southwestern France.

## 1 Analysis of radar backscatter coefficient simulations obtained from the ISBA model coupled to the Water Cloud Model

Under this section, remotely sensed data (ASCAT $\sigma^{\circ}$ and CGLS LAI) are integrated with Surface Soil Moisture (SSM) outputs from the ISBA LSM in order to simulate C-band radar backscatter coefficient ( $\sigma^{\circ}$ ) at an incidence angle of $40^{\circ}$ and VV polarization over the Euro-Mediterranean area. It must be noticed that soil freezing events and complex topography areas are filtered out (Shamambo et al. 2019). The Water Cloud Model (WCM) is used as a potential forward model for estimating $\sigma^{\circ}$ values in the ISBA LSM. The Shuffled Complex Evolution Model Calibrating Algorithm (SCE-UA) is applied with a focus on optimizing the WCM parameters during the modelling process of $\sigma^{\circ}$. The $\sigma^{\circ}$ values resulting from WCM simulations are compared to ASCAT $\sigma^{\circ}$ observations using the Pearson correlation coefficient (R), the root mean square deviation (RMSD) and the standard deviation (SDD). Values of the simulated and observed $\sigma^{\circ}$ are expressed in dB units when calculating the RMSD and SDD scores. The objective is to assess to what extent the simple WCM can be used to simulate $\sigma^{\circ}$ observations over the Euro-Mediterranean area.

### 1.1 The Euro-Mediterranean area

The Euro-Mediterranean area is a large domain with varying land cover, climates, soil types and vegetation biomass. The main land surface types of the Euro-Mediterranean area are presented in Figure III.1.

Figure III.1a shows 14 surface types considered during the development of the ECOCLIMAP II database (Faroux et al. 2013). To produce this map, Faroux et al. used data from the CLC2000 (Corine Land Cover, 2000 version) and GLC2000 (Global Land Cover, 2000 version) land cover maps. The combination of these two maps has a spatial resolution of about $1 \mathrm{~km} \times 1 \mathrm{~km}$. Urban areas are considered together with bare soil, rocks, permanent snow and glaciers, wetlands, and water bodies. The 8 other surface types consist of vegetation classes: needleleaf forest, broadleaf forests, mixed forests, grasslands and shrublands, crops, irrigated crops, mainly crops with a mosaic of natural vegetation types, mainly forests with a mosaic of other vegetation types.

Figure III.1b shows the dominant vegetation type at a spatial resolution of $50 \mathrm{~km} \times$ 50 km as derived by Szczypta et al. (2014) from ECOCLIMAP-II over the same domain. This spatial resolution is more consistent with the low resolution of the ASCAT $\sigma^{\circ}$ observations. The latter map is representative of the main 4 nature types to be considered at this scale: grasslands, crops, forests, and sparse vegetation. Each type may correspond to a large variety of plant species and to contrasting climatic conditions. It can be observed that high vegetation (forests) is mostly dominant at relatively high latitudes (from about $56^{\circ} \mathrm{N}$ to $66^{\circ} \mathrm{N}$ ), from Sweden to the Ural Mountains. This corresponds to boreal forests. Crops tend to dominate landscapes in Ukraine and southern Russia, in large parts of central Europe (e.g. Hungary), Germany, France, and Spain. The grassland nature type includes meadows, steppes and tundra. This type is mostly dominant at high latitudes, in mountainous areas of western and central Europe (e.g. the Alps, the Carpathians), in North Africa, and in the Middle-East.


Figure III. 1 - Vegetation of the Euro-Mediterranean area ( $11^{\circ} \mathbf{W}-62^{\circ} \mathrm{W}, \mathbf{2 5}^{\circ} \mathrm{N}-75^{\circ} \mathrm{N}$ ): (a) land surface types derived from CLC2000 and GLC2000 at a spatial resolution of about $1 \mathrm{~km} \times 1 \mathrm{~km}$ (adapted from Faroux et al. 2013), (b) dominant vegetation type (either grasslands, crops, forests, or sparse vegetation) at a spatial resolution of $0.5^{\circ} \times$ $0.5^{\circ}$ as derived from ECOCLIMAP II (adapted from Szczypta et al. 2014).

### 1.2 Implementation of the WCM

The WCM is described in Section 4 of Chapter II. Copernicus Global Land Service LAI observations and SSM simulations from the ISBA LSM were used as ancillary datasets when calibrating the WCM, with the SCE-UA method serving as the optimization technique. The same flowchart of datasets and methods as used in Shamambo et al. (2019) over southwestern France were applied over the Euro-Mediterranean area for model calibration (Figure III.2), using ASCAT data from 2008 to 2018. The approach which involves

- fitting the WCM parameters all at once (hereafter referred to as Approach 1)
- using the WCM where $V_{1}=\mathbf{1}$ (hereafter referred to as Option 1)
was employed for the experiment over the Euro-Mediterranean area because these two options provided more robust results when implementing the WCM model. The Sections that follow outline the different results obtained from the experiment made over the EuroMediterranean area.


Figure III. 2 - Data flow of the calibration of the water cloud model (WCM): four parameters are tuned $(A, B, C, D)$ using the forcing of ASCAT C-band VV $\boldsymbol{\sigma}^{\circ}$ observations at an incidence angle of $40^{\circ}$, simulated surface soil moisture (SSM), and leaf area index (LAI) observations.

### 1.3 Parameter Values

The outcome of the retrieval of $A$ and $B$ vegetation parameters are values ranging from 0.0 to 0.53 and from 0.00 to 4.12 , respectively (Table III.1). Soil moisture $C$ and $D$ parameters have values varying from -24.4 to -9.54 and from 15.0 to 32.7 , respectively (Table III.1).

Figure III. 3 provides a visual frequency distribution of WCM parameter values. The large (small) skewness score of parameter $B(D)$ (Table III.1) implies that the frequency distribution of this parameter is not Gaussian and that few values much larger (smaller) than the mean value can be observed. The frequency distribution of $B$ is bimodal. While most $B$ values range from 0 to 0.9 , another category of $B$ values mainly ranging from 0.9 to 1.6 is observed.

Figures III.4-7 shows maps of the WCM parameters. The color scales of the subfigures have been suited to those of Figure 4 in Shamambo et al. (2019) in order to assess the potential of observing the same geographical patterns as observed over the study related to southwestern France. The statistical distribution of parameter $A$ shows large values over areas in northern Russia. The latter present dominant forest vegetation coverage as shown in Figure III.1. Such large values are not observed over Scandinavian forests. Urban areas also display high values of the A parameter, as in Shamambo et al. (2019).
Small values of $A, B$ and $C$ parameters below $0.08,0.2$ and -19.5 dB , respectively (Figures III.4,5,6), are mainly observed over the steppes (sparse vegetation and grasslands) at the North and East of the Caspian Sea.

The lowest values of the $D$ parameter, below 25 dB , are mainly observed over the cereal croplands of Lithuania and southern Russia (Figures III.7). The largest values of the $B$ parameter, above 0.9 , are mainly found in central and southeastern Spain and in northern Sweden (Figures III.5).


Figure III. 3 - WCM parameters: histograms of calibrated values over the 2008-2018 calibration time period (in red) over Euro-Mediterranean area at a spatial resolution of $25 \mathrm{~km} \times 25 \mathrm{~km}$ (representing 59792 grid cells).

Table III. 1 - Water cloud model (WCM) parameters ( $A, B, C$, and $D$ ) over the EuroMediterranean area: minimum, median, and maximum values, together with standard deviation and skewness scores.

| Time Period | Parameter | Median <br> [Minimum, Maximum] | Standard deviation | Skewness |
| :--- | :---: | :---: | :---: | :---: |
| $2008-2018$ <br> (calibration period) | $A$ | $0.13[0.00,0.53]$ | 0.04 | -0.46 |
|  | $B$ | $0.52[0.00,4.12]$ | 0.43 | 2.16 |
|  | $C(\mathrm{~dB})$ | $-18.3[-24.4,-9,54]$ | 1.68 | -0.11 |
|  | $D(\mathrm{~dB})$ | $26.9[15.0,32.7]$ | 1.54 | -1.16 |



|  |  |  |  |  |  |  |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| 0.08 | 0.10 | 0.12 | 0.14 | 0.16 | 0.18 | 0.20 |

Figure III. 4 - WCM parameters: calibrated values for 2008-2018 over the EuroMediterranean area of parameter $\boldsymbol{A}$.


Figure III. 5 - WCM parameters: calibrated values for 2008-2018 over the EuroMediterranean area of parameter B.


Figure III. 6 - WCM parameters: calibrated values for 2008-2018 over the EuroMediterranean area of parameter $\boldsymbol{C}$.


Figure III. 7 - WCM parameters: calibrated values for 2008-2018 over the EuroMediterranean area of parameter $D$.

The overall and seasonal performance of the calibrated WCM can be assessed from the scores given in Table III.2. Observed and simulated $\sigma^{\circ}$ values are compared for the period from 2008 to 2018 using the $R$ and RMSD scores. Freezing conditions and topography above 1200 m a.s.l. are masked in order to prevent these conditions from affecting the obtained results. Evaluation is made over the pooled dataset (All) and over two subgroups corresponding to springtime (i.e., March, April and May denoted by MAM) and summertime (i.e. June, July and August (JJA)). The MAM and JJA time periods correspond to $23 \%$ and $44 \%$ of the total number of observations, respectively. The smaller number of observations at spring is caused by the sorting out of soil freezing events mainly occurring at high latitudes. Table III. 2 indicates that the WCM performs better at spring with median $R$ value of 0.58 than in summertime where a median $R$ value of 0.44 is obtained. While most $R$ values are larger than 0 , markedly negative values of correlation $(R<-0.5)$ can be observed for both summer and spring seasons. Conversely, the RMSD score shows better values in the summertime than at spring ( 0.37 and 0.54 dB , respectively).

In Figure III.8, maps of mean ASCAT $\sigma^{\circ}$ observations and of simulated $\sigma^{\circ}$ values are compared for spring and summertime. Highest values of both simulated $\sigma^{\circ}$ and ASCAT $\sigma^{\circ}$ observations are representative of urban areas (see black spots corresponding for example to London, Paris, and Moscow). Seasonal correlation maps and RMSD maps for spring and summertime are also shown. Generally, the correlation results are good, except for some specific regions where small and negative correlations can be observed for both seasons (e.g. central and southeastern Spain, Ural and Scandinavia). Mainly small RMSD values are noticed for both spring and summer seasons, except for areas with low A values that correspond to steppes of Kazakhstan and to cereal croplands of Ukraine and southern Russia, as seen in Figure III.4. The mean $\sigma^{\circ}$ bias maps (e and f subfigures) between simulated and observed $\sigma^{\circ}$ mainly show a small seasonal bias. However, over some regions during spring, relatively high values above 0.7 are seen. The same areas tend to present a negative bias at summertime. The areas having a seasonal bias seem to be representative of agricultural areas covered by straw cereals such as wheat. This is consistent with the results of Shamambo et al. (2019) over southwestern France.

Table III. 2 - WCM performance: statistical scores ( $R$ and RMSD) of simulated $\sigma^{\circ}$ values over Euro-Mediterranean area. The calibration period of the parameters is from 2008 to 2018. The calibration scores are given for the pooled dataset (All) and for the March, April, and May (MAM) spring period and the June, July, and August (JJA) summer period. The total number of daily observations used to calculate the scores is indicated ( $n$ ).

| Scores | Median $R$ value <br> $(n)$ |  |  | Median RMSD value in dB |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Calibration <br> $(2008-2018)$ | All | MAM | JJA | All | MAM | JJA |
|  | 0.55 | 0.58 | 0.44 | 0.43 | 0.54 | 0.37 |
|  | $(50241803)$ | $(11352435)$ | $(22080490)$ |  |  |  |

(a)

(b)


|  |  |  |  |  |
| :--- | :--- | :--- | :--- | :--- |
| -14 | -12 | -10 | -8 | -6 |
|  |  | Decibels [dB] |  |  |
|  |  |  |  |  |

(c)

(d)


|  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: |
| -14 | -12 | -10 | -8 | -6 |
|  | Decibels [dB] |  |  |  |
|  |  |  |  |  |

(e)

(f)

Difference in Sigma0 (Sim-Obs) [JJA]


|  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: |
| -0.8 | -0.4 | 0.0 | 0.4 | 0.8 |
|  |  |  |  |  |
|  |  |  |  |  |
|  |  |  |  |  |
| Decibels [dB] |  |  |  |  |

(g)

(h)

(i)

(j)



Figure III. 8 - WCM performance: (a,b) observed $\sigma^{\circ}$ from Advanced Scatterometer (ASCAT) (sigma0_OBS), (c, d) simulated $\sigma^{\circ}$ (sigma0_FIT), (e, f) mean bias (simulations-observations), (g, h) temporal correlation, (i, j) RMSD, for (a, c, e) the March, April, and May (MAM) spring period and for (b, d, f) the June, July, and August (JJA) summer period. All values are averaged or calculated for the period from 2008 to 2018.

Figure III. 9 below presents monthly time-series of spatially averaged simulated and observed $\sigma^{\circ}$ over the Euro-Mediterranean area. The two time series are highly correlated ( $R$ $=0.93$ ), with $\mathrm{RMSD}=0.20 \mathrm{~dB}$. At spring, the simulated $\sigma^{\circ}$ values are slightly larger than the observed ones and vice versa during the autumn. Again, this seasonal bias is related to agricultural areas covered by straw cereals (Figure III.8). On the other hand, there seems to be a temporal trend in the observed $\sigma^{\circ}$ anomalies with respect to the simulations. From 2008 to 2011 , the observed anomaly curve is nearly always below the simulated one and vice versa from 2016 to 2018. This means that the ASCAT $\sigma^{\circ}$ values tend to increase and that this trend cannot be explained by the model. The difference between simulated and observed values and the trend in $\sigma^{\circ}$ observations tend to produce rather poor scores of monthly scaled anomaly time-series ( $R=0.55$ and $\mathrm{RMSD}=0.90$ ), even if the simulated $\sigma^{\circ}$ variability is visually consistent with the observed variability.

Monthly time-series


Monthly time-series (anomalies)


Figure III. 9 - WCM performance: $\sigma^{\circ}$ simulated by the WCM (red lines and dots) vs. ASCAT $\sigma^{\circ}$ observations (blue lines and dots) over the Euro-Mediterranean area from 2008 to 2018. (a) monthly mean values. (b) Scaled monthly anomalies.

### 1.5 Interpretation of results

The WCM parameter maps presented in Section 1.3 (Figures III. 4 to III.7) present rather clear geographical patterns. The geographic information is provided by the forcing datasets:

- the SSM values generated by the ISBA LSM are expressed in $\mathrm{m}^{3} \mathrm{~m}^{-3}$ and depend on model-dependent pedotransfer functions using soil texture and soil organic matter maps
- the satellite derived LAI
- the ASCAT $\sigma^{\circ}$ observations.

It is interesting to compare the WCM parameter values to known geographical features. In particular, the regions of the steppes of Kazakhstan and the cereal croplands of Ukraine and southern Russia present distinct properties.

Figure III.8a,b shows that the smallest mean $\sigma^{\circ}$ values (either observed or simulated) are observed in the steppes of Kazakhstan and, to some extent, over the cereal croplands of Ukraine and southern Russia, with mean $\sigma^{\circ}$ values of -14 dB or less. These regions correspond to low values of the A parameter (Figure III.4) and to large RMSD values (Figure III.8i,j). The low $\sigma^{\circ}$ values could be explained by the fact that these areas correspond to frequently dry soils in relation to the semi-arid climate of these regions. For example, the total yearly precipitation at the weather station of $\operatorname{Sam}\left(45.40^{\circ} \mathrm{N}, 56.12^{\circ} \mathrm{E}, 88\right.$ m a.s.l.), in Kasakhstan, between the Caspian and the Aral Sea, is about 120 mm per year (https://www.meteoblue.com/en/weather/historyclimate/climateobserved/letnikyrgyzbay kazakhstan_12144212, last access 27 August 2020). Further north in Russia, mean precipitation does not exceed 300 mm per year at Orenburg $\left(51.68^{\circ} \mathrm{N}, 55.10^{\circ} \mathrm{E}, 117 \mathrm{~m}\right.$ a.s.l.) (https://www.meteoblue.com/en/weather/historyclimate/climateobserved/orenburg-\%2F-tsentralny russia 6301024, last access 27 August 2020). Dry soils do not necessarily mean that very low $\sigma^{\circ}$ values are observed. The dry asymptotic $\sigma^{\circ}$ value of soils is represented by the $C$ parameter in the WCM. Figure III. 6 shows that $C$ values is these regions are quite small ( -19.5 dB or less). The vegetation itself presents small effective $\sigma^{\circ}$ values: the $A$ parameter represents the asymptotic $\sigma^{\circ}$ value of vegetation when vegetation is sufficiently dense to be completely opaque at C-band (i.e. $t^{2}=0$ in the WCM). For example, values of $A$ less than 0.08 (in linear unit) observed in these regions (Figure III.4) correspond to asymptotic $\sigma^{\circ}$ value smaller than -12 dB . The large RMSD values observed over these regions correspond to a marked seasonal bias of the WCM (Figure III.8e,f). This could be explained by the fact that the WCM is a semi-empirical model with a simplified representation of the backscatter characteristics and of the soil and vegetation properties. For example, it is assumed that $\mathrm{VOD}=B \times \mathrm{LAI}$ and that $B$ is a constant. In reality, the $B$ parameter may present a seasonal variability. Also, VOD is probably more influenced by the vegetation water content (VWC) than by LAI. Even if VWC and LAI are related, the ratio of VWC to LAI may change from one season to another and from one plant growth stage to another, especially for low herbaceous vegetation. This was shown in southwestern France by Zakharova et al. (2012) using observations from an airborne L-band radiometer.

An interesting feature of the $B$ vegetation parameter derived from the ASCAT observations in Figure III. 3 is that the largest values ( $B>1.2$ ) are found in contrasting climatic conditions (Figure III.1):

- arid areas in Spain, North Africa and the Middle-East
- boreal regions covered by needleleaf trees (Taiga).

A common characteristic of the vegetation covering these regions is the rather small and thick leaves. The plant trait that can be used to quantify this characteristic is the Specific Leaf Area (SLA). Boreal needleleaf trees present a typical value of SLA $=5 \mathrm{~m}^{2} \mathrm{~kg}^{-1}$. This is the value used in the ISBA model (Delire et al. 2020). This is much less than the values used for boreal broadleaf cold deciduous trees (SLA $=15.4 \mathrm{~m}^{2} \mathrm{~kg}^{-1}$ ) and cereal crops (SLA $=14.8 \mathrm{~m}^{2} \mathrm{~kg}^{-1}$ ). In Mediterranean and arid areas, sclerophyll vegetation also presents small SLA values. For example, Ackerly et al. (2001) reported mean SLA values of 3.5 and 6.6 $\mathrm{m}^{2} \mathrm{~kg}^{-1}$ for Adenostema fasciculatum and Prunus ilicifolia, respectively. These two shrub species are commonly found in coastal California. Grubb et al. (2015) measured SLA in southern Spain for a large variety of plant species and soil conditions. Values ranged from 2.5 to $13.710 \mathrm{~m}^{2} \mathrm{~kg}^{-1}$ and about $80 \%$ of the values were below $10 \mathrm{~m}^{2} \mathrm{~kg}^{-1}$.

The $D$ soil parameter represents the sensitivity of soil backscatter to changes in SSM. The SSM value is influenced by the soil porosity used in the LSM used to generate this quantity. As a consequence, the $D$ parameter is model-dependent and the map showed in Figure III. 7 could be different if another LSM had been used.

Poor correlations in Figure III.8g,h could be caused by perturbing factors such as:

- specific ground features influencing the radar backscatter at C-band
- radio-frequency interferences (RFI) at C-band
- uncertainties in:
- the semi-empirical WCM caused by physical approximations
- ERA-5 precipitation used to force ISBA SSM simulations
- LAI observations

A specific ground feature that seems to influence the WCM performance is the presence of calcareous karsts (Williams and Ford 2006). These areas often present limestone outcrops. The $R$ score in Figure III.8g,h shows that small and even negative correlations between the observed and simulated $\sigma^{\circ}$ can be observed in southeastern Spain, especially at summertime. This is particularly evident there but also in other areas corresponding to low altitude karstic areas as shown by Figure III.10. The 14 regions indicated in this Figure present small or negative correlations at both spring and summer seasons. An example of low-altitude karstic landscape is given in Figure III.11. Along with large limestone outcrops, smaller calcareous gravels and stones at the soil surface can be observed. This kind of ground structure could impact backscatter. The limited fractional coverage of the soil-plant system and possible fine scale shadowing effects may limit the amount of information that could be derived from the ASCAT $\sigma^{\circ}$. Other impacts of the ground structure on the ASCAT signal have been reported. They mainly concern arid areas such as the Sahara and the Arabian Peninsula (Al-Yaari et al. 2014) and can be explained by sub-scattering effects related to the large penetration depth in dry conditions (Morisson and Wagner 2020). This explanation could also be valid for karstic areas since water tends to infiltrate very rapidly into the soil, especially when limestone rocky outcrops are present (Zhao et al. 2020). This process is not represented in LSMs. It must also be noticed that arid calcareous karsts cover large areas of Western Sahara and of the Arabian Peninsula (Hollingsworth 2009).


Figure III. 10 - Plain and mountainous calcareous areas (adapted from Williams and Ford 2006) (in dark blue) and low-altitude ( $<\mathbf{1 2 0 0} \mathbf{~ m}$ above sea level) mountainous karstic areas (in red) for which low $R$ values of WCM $\sigma^{\circ}$ vs. ASCAT $\sigma^{\circ}$ are observed in Figure III.8: from West to East, 1 - Cantabrian mountains, 2 - Baetic and Iberian Systems and Toledo Mountains, 3 - Pyrenees, 4 - Causses, 5 - Jura, 6 - French Alps and Côte d'Azur, 7 - Northern calcareous Alps, 8 - Dinaric Alps, 9 - Carpathians, 10 - Transylvanian Alps, 11 Southern Greece, 12 - Taurus Mountains, 13 - Caucasus Mountains, 14 - Ural Mountains.


Figure III. 11 - Example of low-altitude karstic area with limestone outcrops in Côte d’Azur (France, 23 km north of Cannes). Photo by J.-C. Calvet, May 2018.

Radio Frequency Interference (RFI) at C-band over land can be observed from space. The RFI can be caused by wireless communication systems, radars, etc. The number of noise outliers and the noise background level observed by the ASCAT instrument tend to increase since the start of the ASCAT time series in 2007 (Ticconi et al. 2017). However, the noise generated by RFI over land is relatively low and Ticconi et al. (2017) suggest that the impact of current RFI on soil moisture retrieval from ASCAT is likely to be small. However, Figure III. 9 shows an increasing trend in $\sigma^{\circ}$ values that cannot be explained by WCM simulations. A trend in RFI noise power could at least partly explain such a trend in $\sigma^{\circ}$ values. Monti-Garnieri et al. (2017) expressed concern about RFI becoming a major issue at C-band on the short term with the development of new generation radio local area networks (RLAN). They developed a method to monitor C-band RFI from Sentinel-1. They present an example over the Euro-Mediterranean area (Figure III.12). The spatial distribution of C-band RFI does not match the low WCM $R$ score value distribution in Figure III.8g,h. This suggests that RFI alone cannot explain the WCM vs. ASCAT $\sigma^{\circ}$ discrepancies.


Figure III. 12 - C-band RFI map over the Euro-Mediterranean area produced from Sentinel-1 data by Monti-Garnieri et al. 2017 (adapted from Fig. 10 in Monti-Garnieri et al. 2017).

Other perturbing factors include uncertainties in ERA-5 precipitation used to force ISBA SSM simulations, uncertainties in the semi-empirical WCM caused by physical approximations, uncertainties in LAI observations. The latter two sources of errors are discussed in Section 2. Regarding ERA5 precipitation, Albergel et al. (2018) and Hersbach et al. (2020) showed that ERA5 performs much better than its predecessor ERA-Interim. However, difficulties in representing specific convective precipitation events and precipitation in mountainous areas cannot be excluded.

### 1.6 Conclusions

Analysis over the Euro-Mediterranean area has demonstrated that the WCM can be used on a large scale to simulate ASCAT $\sigma^{\circ}$ observations under contrasting climate and land surface conditions. As a whole, the performance of WCM is reasonably good with median $R$ and RMSD score values of 0.55 and 0.43 dB , respectively. Over some areas, smaller $R$ values are found and some negative values can even be observed. The regions with lower and negative values of correlations scores can be related to challenging conditions for both hydrological modeling and microwave remote sensing. This is the case for calcareous karstic areas over which both the WCM and the ISBA LSM may have shortcomings. The seasonal average bias shows small values except for wheat croplands. The latter present a positive bias (observations minus simulations) at springtime and a negative bias at summertime. The monthly anomalies of simulated $\sigma^{\circ}$ are consistent with those of ASCAT $\sigma^{\circ}$ and this shows the skill of the WCM in modelling the temporal dynamics of ASCAT $\sigma^{\circ}$ observations. The month to month variability of anomalies is reasonably well represented by the WCM. On the other hand, ASCAT $\sigma^{\circ}$ observations tend to increase from 2008 to 2018 and this trend is not reproduced by the WCM. This could be related to the increasing RFI noise levels. Finally the B vegetation parameter of the WCM, relating LAI to VOD is key. Assuming a constant value for B may be erroneous and could explain the seasonal bias observed over wheat croplands.
The calibration, the performance of the WCM and the perturbing factors are analyzed in more detail over southwestern France in Section 2 below. This region has many contrasting land cover types, contains calcareous karstic areas at low altitude (Causses, Cobières) and the RFI noise level seems to be very low (Figure III.12).

## 2 Detailed analyses of results over southwestern France



Figure III. 13 - Dominant land cover classes over France as derived from ECOCLIMAP-II (Faroux et al. 2013) at a spatial resolution of $1 \mathrm{~km} \times 1 \mathrm{~km}$. The southwestern France area investigated in this Section is indicated (dark line).

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## Summary

A data analysis was carried out over the southwestern France area in order to evaluate the use of ASCAT radar backscatter coefficient ( $\sigma^{\circ}$ ) observations for observing, simulating and understanding the dynamics of the land surface process over this area of interest. The water cloud model (WCM) was used to simulate ASCAT $\sigma^{\circ}$ observations using leaf area index and surface soil moisture land surface variables. The impact of these independent LSVs was investigated over contrasting vegetation land cover types. The used LAI and surface soil moisture data were from CGLS satellite observations and from the ISBA LSM, respectively. In a first step, the potential of retrieving values of the four parameters of the WCM model was investigated. The Shuffled Complex Evolution Model Calibrating Algorithm (SCE-UA) was implemented with a focus on optimizing the estimation of the WCM parameters during the modelling process of $\sigma^{\circ}$. Realistic and robust values of four parameters of the WCM were obtained over southwestern France. Values did not change much in response to the time period considered, either with the calibration period (20102013) or with the whole analysis period (2010-2016). Secondly, the performance of the WCM over different seasons was assessed. It was found that simulated $\sigma^{\circ}$ maps were quite similar to the observations but that a seasonal mean bias existed between the two over agricultural areas mainly covered by wheat croplands. Experiments over these agricultural areas showed that the WCM tended to overestimate $\sigma^{\circ}$ values in the springtime and underestimate $\sigma^{\circ}$ values in the summertime. Furthermore, it was found that WCM has shortcoming over karstic areas with small or negative correlations values found in locations corresponding to such zones. Lastly, the impact of the Klaus storm on the ASCAT observations over the Landes forest in 2009 was investigated. Analysis showing the difference in $\sigma^{\circ}$ between the zone affected by the storm and the average of two zones not affected by the storm showed the impact of the Klaus storm on the signal. After the storm on 24 January 2009, a loss of the seasonal cycle on ASCAT $\sigma^{\circ}$ differences was observed. The seasonality was seen to be restored after at least 4 years. Differences in LAI of the Storm area with respect to bordering agricultural areas presented a discontinuity in correspondence with the storm period. Before the storm, higher values of the LAI difference annual cycle were observed than after the Klaus storm. A reduction in LAI values was observed and was the result of forest degradation after the storm. The reduction in the LAI annual seasonal cycle was found to drive the ability of the WCM to simulate changes in $\sigma^{\circ}$ differences during the forest degradation period from 2009 to 2012. During the regeneration period (2013 onward), the WCM needed to be recalibrated in order to reproduce the observations. A larger $B$ value was obtained, that could be related to the presence of younger trees. This study demonstrated that the WCM was able to simulate ASCAT $\sigma^{\circ}$ observations and that the latter are sensitive to land cover changes. The final conclusion from this study was that the WCM may also be used as an observation operator in the context of assimilating $\sigma^{\circ}$ observations into the ISBA LSM.

## Résumé

Une analyse de données est menée dans le sud-ouest de la France afin d'évaluer l'utilisation d'observations des coefficients de rétrodiffusion radar ASCAT ( $\sigma^{\circ}$ ) pour observer, simuler et comprendre la dynamique des processus de surface sur cette zone d'intérêt. Le modèle de nuage d'eau (Water Cloud Model, WCM) est utilisé pour simuler les observations de $\sigma^{\circ}$ ASCAT en utilisant deux variables des surfaces terrestres : l'indice de surface foliaire de la végétation (Leaf Area Index, LAI) et l'humidité superficielle du sol. L'impact de ces variables indépendantes est examiné pour plusieurs types de végétation différents. Les données de LAI proviennent de la base de produits satellitaires CGLS. L'humidité superficielle du sol est simulée par le modèle ISBA des surfaces terrestres. Dans un premier temps, la possibilité d'estimer les valeurs des quatre paramètres du WCM est évaluée. L'algorithme de minimisation Shuffled Complex Evolution Model Calibrating Algorithm (SCE-UA) est mis en oeuvre dans le but de cartographier les valeurs de ces paramètres par inversion du WCM sur la base des observations de $\sigma^{\circ}$. Des valeurs réalistes et stables des quatre paramètres du WCM sont obtenues sur le sud-ouest de la France. Les valeurs obtenues durant la période d'étalonnage (2010-2013) ne varient pas fortement si l'on considère une période plus longue (2010-2016). D'autre part, la performance du WCM en fonction des saisons est étudiée. Les cartes de $\sigma^{\circ}$ simulés sont très similaires aux observations mais un biais saisonnier existe avec les observations sur les zones de cultures céréalières. L'analyse de ces zones montre que le WCM a tendance à surestimer les valeurs de $\sigma^{\circ}$ au printemps et de les sous-estimer en été. On montre aussi que le WCM est moins efficace sur les zones karstiques car le coefficient de corrélation avec les observations y est faible voire négatif. Enfin, l'impact de la tempête Klaus en 2009 sur la forêt des Landes est visible dans les observations ASCAT lorsqu'on considère la différence de $\sigma^{\circ}$ entre la zone de la forêt la plus impactée par la tempête et les zones agricoles adjacentes. Après le 24 janvier 2009, date de la tempête, on observe la perte du cycle saisonnier de la différence de $\sigma^{\circ}$ observée. La saisonnalité ne réapparaît qu'après 4 années. Les différences de LAI entre la zone affectée par la tempête et les zones agricoles adjacentes présentent aussi une discontinuité après la tempête. Après la tempête, la variabilité saisonnière de cette différence est moins marquée qu'avant la tempête. Une diminution des valeurs de LAI à cause de la dégradation du couvert forestier est observée. On montre qu'il est important de fournir cette information au WCM pour qu'il puisse simuler correctement l'effet de la tempête et la phase de dégradation qui a suivi jusqu'en 2012. Durant la phase de régénération qui commence en 2013, il est nécessaire de ré-étalonner le WCM afin de reproduire les observations. On obtient alors une valeur plus grande du paramètre $B$, qui pourrait correspondre à la présence d'arbres plus jeunes. Cette étude montre que le WCM est capable de simuler les observations de $\sigma^{\circ}$ ASCAT et que ces dernières sont sensibles à des changements d'occupation des terres. En conclusion, on montre que le WCM pourrait être utilisé comme un opérateur d'observation dans le contexte de l'assimilation d'observations de $\sigma^{\circ}$ dans le modèle ISBA des surfaces terrestres.
remote sensing

## Article

# Interpretation of ASCAT Radar Scatterometer Observations Over Land: A Case Study Over Southwestern France 

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#### Abstract

This paper investigates to what extent soil moisture and vegetation density information can be extracted from the Advanced Scatterometer (ASCAT) satellite-derived radar backscatter ( $\sigma^{\circ}$ ) in a data assimilation context. The impact of independent estimates of the surface soil moisture (SSM) and leaf area index (LAI) of diverse vegetation types on ASCAT $\sigma^{\circ}$ observations is simulated over southwestern France using the water cloud model (WCM). The LAI and SSM variables used by the WCM are derived from satellite observations and from the Interactions between Soil, Biosphere, and Atmosphere (ISBA) land surface model, respectively. They permit the calibration of the four parameters of the WCM describing static soil and vegetation characteristics. A seasonal analysis of the model scores shows that the WCM has shortcomings over karstic areas and wheat croplands. In the studied area, the Klaus windstorm in January 2009 damaged a large fraction of the Landes forest. The ability of the WCM to represent the impact of Klaus and to simulate ASCAT $\sigma^{\circ}$ observations in contrasting land-cover conditions is explored. The difference in $\sigma^{\circ}$ observations between the forest zone affected by the storm and the bordering agricultural areas presents a marked seasonality before the storm. The difference is small in the springtime (from March to May) and large in the autumn (September to November) and wintertime (December to February). After the storm, hardly any seasonality was observed over four years. This study shows that the WCM is able to simulate this extreme event. It is concluded that the WCM could be used as an observation operator for the assimilation of ASCAT $\sigma^{\circ}$ observations into the ISBA land surface model.


Keywords: ASCAT; radar scatterometer; soil moisture; leaf area index; model inversion

## 1. Introduction

The main mission of space-borne radar scatterometers is to monitor wind speed over the oceans [1]. It was shown that wind scatterometers operating at the C-band frequency ( $\sim 5 \mathrm{GHz}$ ) such as the Advanced Scatterometer (ASCAT) can be used over land to monitor variables such as surface soil moisture (SSM) [2] and vegetation optical depth (VOD) [3]. The ASCAT C-band radar VOD can be related to vegetation water content (VWC) as well as to the leaf area index (LAI) [3]. Both SSM and LAI can be integrated into land surface models (LSMs) in order to analyze key variables such as the root-zone soil moisture and the vegetation above-ground biomass. Barbu et al. [4] showed the feasibility of implementing the joint sequential assimilation of SSM and LAI into the Interactions between Soil, Biosphere, and Atmosphere (ISBA) LSM within the Surface Externalisée (SURFEX)
modeling platform [5]. Their work permitted the development of a Land Data Assimilation System (LDAS). Albergel et al. [6] further extended the LDAS at a global scale (LDAS-Monde) and showed that the assimilation of LAI observations can be used to analyze the root-zone soil moisture in addition to the vegetation above-ground biomass. This also means that LDAS-Monde could potentially use the information content of C-band backscatter observations ( $\sigma^{\circ}$ ) to analyze vegetation variables together with the root-zone soil moisture [6]. To achieve this goal, an observation operator such as the water cloud model (WCM) [7] is needed for predicting $\sigma^{\circ}$ from LSMs. SSM and LAI observations can be assimilated into the ISBA LSM because these two variables can be predicted by ISBA. It must be noted that the current version of ISBA is not able to simulate the VWC.

The simulation of the radar backscatter signal requires a radiative transfer model that calculates the propagation of radiation (in this case, microwave radiation) through a plant canopy. In this study, the semi-empirical WCM proposed by Attema and Ulaby [7] is used to simulate the impact of SSM and LAI on the total radar backscatter signal $\sigma^{\circ}$. Lievens et al. [8] used a version of the WCM to simulate ASCAT $\sigma^{\circ}$ from simulated SSM values and VOD observations from passive microwave instruments. Vreugdenhil et al. [3] showed that C-band VOD values derived from ASCAT $\sigma^{\circ}$ using the WCM are correlated with satellite-derived LAI observations from the Copernicus Global Land service [9] over Australia. The VOD versus LAI correlation was particularly good for grasslands, but a time lag was observed for crops and forests. A possible explanation for the mismatch between VOD and LAI time series was that VOD at C-band may be sensitive to non-photosynthetic vegetation parts (e.g., branches in the case of forests) in addition to leaves. Finally, the WCM may not be able to represent all components of scattering within vegetation canopies [10].

The objectives of this study are to investigate

- The ability of the WCM to simulate ASCAT $\sigma^{\circ}$ observations using SSM values simulated by the ISBA LSM and satellite-derived LAI, in contrasting land-cover conditions over southwestern France,
- The statistical distribution of the parameters of the WCM,
- The response of observed and simulated $\sigma^{\circ}$ to LAI and SSM across seasons,
- The response of observed and simulated $\sigma^{\circ}$ to a rapid change in vegetation cover, and
- The feasibility of building an observation operator for the assimilation of ASCAT $\sigma^{\circ}$ observations into the ISBA LSM.

In a first stage, a standard calibration method is used in order to fit the parameters of the WCM. The calibrated WCM is evaluated using $\sigma^{\circ}$ observations not used during the calibration process. In a second stage, the capacity of $\sigma^{\circ}$ observations to detect vegetation changes and the capacity of the WCM to simulate such impacts on $\sigma^{\circ}$ are evaluated over an area of the Landes forest affected by the Klaus windstorm event of 24 January 2009.

The data and methods are presented in Section 2. The results are presented in Section 3 and discussed in Section 4. Finally, the main conclusions are summarized in Section 5.

## 2. Material and Methods

### 2.1. Study Area

The study area is located in southwestern France, $42.00^{\circ} \mathrm{N}$ to $46.00^{\circ} \mathrm{N}$ and $2.00^{\circ} \mathrm{W}$ to $4.00^{\circ} \mathrm{E}$ (Figure 1). The main vegetation types consist of crops such as maize and wheat, grasslands, coniferous trees, and broadleaf trees [11]. The large Landes coniferous forest covers the western part of the domain. The Landes forest mainly consists of maritime-pine (Pinus pinaster) trees in sandy soils [12]. This forest was damaged by the Klaus windstorm event of 24 January 2009. The "Storm" zone $\left(43.80^{\circ} \mathrm{N}-44.25^{\circ} \mathrm{N}, 1.00^{\circ} \mathrm{W}-0.40^{\circ} \mathrm{W}\right)$ indicated in Figure 1 corresponds to the forest area that was most affected by Klaus [13]. Two zones, "North" ( $\left.44.55^{\circ} \mathrm{N}-45.00^{\circ} \mathrm{N}, 0.75^{\circ} \mathrm{W}-0.15^{\circ} \mathrm{W}\right)$ and "South" $\left(43.40^{\circ} \mathrm{N}-43.85^{\circ} \mathrm{N}, 0.30^{\circ} \mathrm{W}-0.30^{\circ} \mathrm{E}\right)$, are also selected for further analysis of the impact of Klaus, following Teuling et al. [13]. These two zones are mainly composed of crop and grassland land-cover
types, with the North zone also including urban and forested areas. The South zone corresponds to the Bas-Armagnac agricultural area. Agricultural areas present contrasting crop rotation systems. For example, the south of the Landes forest (including Bas-Armagnac) is mainly covered by maize monoculture, with some areas covered by vineyards. Grassland and forest patches are found over the steepest slopes. Further east, C3 crops such as wheat are dominant. This is the case of the Lomagne agricultural area. Crop rotation in Lomagne is characterized by winter crops such as wheat, barley, and rapeseed and summer crops such as maize, sorghum, and sunflower. Areas presenting a mean elevation greater than 1200 m above sea level (a.s.l.) are excluded from the analysis. They are found in the Pyrenees Mountains.


Figure 1. Southwestern France: study area (a) and location of the "Storm" Landes forest site (b). "Storm" refers to the forest area most affected by the Klaus storm. "North" and "South" are bordering agricultural areas. Fractional area of the main vegetation types is shown in ( $\mathbf{c}-\mathbf{h}$ ), adapted from [11].

### 2.2. SSM Simulations

The ISBA LSM was developed at the National Center for Meteorological Research (CNRM) and is a part of the SURFace Externalisée (SURFEX) modeling platform of Meteo-France [5]. In this study, a carbon dioxide responsive version of the ISBA LSM [14,15] in SURFEX version 8.1 is used to simulate SSM together with the surface soil ice content and LAI. Only SSM is used in this work, from the model topsoil layer comprised between 1 and 4 cm depth. The simulated topsoil temperature and ice content in the shallow ( 1 cm thick) surface soil layer are used to exclude soil-freezing conditions from the analysis. The ISBA model runs are driven by ERA-5 [16], which is the latest atmospheric reanalysis from the European Center For Medium-Range Weather Forecast (ECMWF). The ISBA simulations cover southwestern France from 2007 to 2016 at a spatial resolution of $0.25^{\circ} \times 0.25^{\circ}$.

### 2.3. ASCAT $\sigma^{\circ}$ Observations

ASCAT is a real aperture radar on board the Meteorological Operational Satellite Program of Europe (Metop) series of satellites. It operates at a frequency of 5.255 GHz in C-band and uses vertically
polarized antennas for transmission and reception, producing like-polarized VV radar backscatter ( $\sigma^{\circ}$ ) observations. The first Metop satellite, called Metop-A, has been operational since 2006. Metop-B and Metop-C were launched in 2012 and 2018, respectively. The ASCAT sensors have two sets of three antennae, measuring $\sigma^{\circ}$ at three azimuth angles of $45^{\circ}, 90^{\circ}$, and $135^{\circ}$ over two 550 km wide swaths separated by a gap of about 360 km from the satellite ground track for a minimum orbit height. Measurements of $\sigma^{\circ}$ are done over a wide range of incidence angles varying from $25^{\circ}$ to $65^{\circ}$. The ASCAT backscatter observations are available at full resolution, together with spatially weighted measurements at $25 \mathrm{~km} \times 25 \mathrm{~km}$ or $50 \mathrm{~km} \times 50 \mathrm{~km}$ resolution [2,17]. In this study, we used an ASCAT $\sigma^{\circ}$ dataset normalized to an incidence angle of $40^{\circ}$, which was provided by the Vienna University of Technology. The dataset is sampled on a discrete global grid ( $12.5 \mathrm{~km} \times 12.5 \mathrm{~km}$ ) at a spatial resolution of $25 \mathrm{~km} \times 25 \mathrm{~km}$. The incidence angle normalization is done by using a second-order polynomial describing the relationship between incidence angle and backscatter [18]. The $\sigma^{\circ}$ dataset consists of mean daily values incorporating data from ascending and descending orbits. In order to adapt the normalized ASCAT $\sigma^{\circ}$ data to the $0.25^{\circ} \times 0.25^{\circ}$ grid used by the ISBA model, the data were interpolated by an arithmetic average to the model grid points. Further processing was made to mask the ASCAT $\sigma^{\circ}$ data for areas with frozen soils and very complex topography so as to avoid these perturbing factors influencing the results.

### 2.4. LAI Observations

The satellite-derived LAI product referred to as GEOV2 is produced by the Copernicus Global Land Service (CGLS) (http://land.copernicus.eu/global/). The GEOV2 LAI is available every 10 days at a spatial resolution of $1 \mathrm{~km} \times 1 \mathrm{~km}$. A neural network retrieval technique [9] is used to derive the GEOV2 LAI product from SPOT-VGT sensors (from 1999 to 2014) and PROBA-V sensors (from 2014 to present). Validation studies made by Camacho et al. [19] demonstrated that this LAI product tends to perform better than other products, with a root mean square deviation (RMSD) with respect to in situ observations across contrasting biomes of about $0.7 \mathrm{~m}^{2} \mathrm{~m}^{-2}$. This LAI product was integrated into the ISBA LSM in a number of studies $[6,20,21]$ using a sequential data assimilation technique. In this study, the LAI product was interpolated by an arithmetic average to the $0.25^{\circ} \times 0.25^{\circ}$ model grid points. A discussion on the added value of this product can be found in Section 4.4.

### 2.5. The Water Cloud Model (WCM)

Several models can be used to model radar backscatter signals over land [22-24]. The WCM stands out as a robust approach because of its simplicity: it needs few parameters to be fitted and uses few biophysical variables. It can be used as an inversion model to retrieve vegetation and soil moisture variables at various wavelengths [25-31]. The WCM assumes that the vegetation canopy can be modeled as a collection of water droplets that are uniformly distributed within the canopy. Generally, the radar backscattering from a vegetated soil surface comprises (1) the direct backscatter of the vegetation $\left(\sigma_{\text {veg }}^{0}\right)$, (2) the backscatter of the soil $\left(\sigma_{\text {soil }}^{0}\right)$, which is attenuated twice by the vegetation layer, in relation to the vegetation transmissivity $(t)$ depending on the incidence angle $(\theta)$ and on the vegetation optical depth (VOD), and (3) multiple scattering from vegetation-ground interactions $\left(\sigma_{\text {veg }+ \text { soil }}^{0}\right)$ :

$$
\begin{equation*}
\sigma^{0}=\sigma_{v e g}^{0}+t^{2} \sigma_{\text {soil }}^{0}+\sigma_{\text {soil }+ \text { veg }}^{0} \tag{1}
\end{equation*}
$$

with

$$
\begin{gather*}
\sigma_{\text {soil }(d B)}^{0}=10 \log _{10} \sigma_{\text {soil }}^{0}=C+D \times S S M  \tag{2}\\
t=e^{-\frac{V O D}{\cos \theta}}  \tag{3}\\
\sigma_{\text {veg }}^{0}=A V_{1} \cos \theta\left(1-t^{2}\right) \tag{4}
\end{gather*}
$$

and

$$
\begin{equation*}
V O D=B V_{2} . \tag{5}
\end{equation*}
$$

It must be noted that in Equations (1) and (2), $\sigma_{\text {soil }}^{0}$ is expressed in linear units, while in Equation (2), $\sigma_{\text {soil }(d B)}^{0}$ is expressed in dB units. SSM is the volumetric soil moisture, which in this study is representative of the top $1-4 \mathrm{~cm}$ layer of the soil in the ISBA LSM.

It is assumed that the double-bounce term can be neglected:

$$
\begin{equation*}
\sigma_{v e g+\text { soil }}^{0} \ll \sigma^{0} . \tag{6}
\end{equation*}
$$

Since the WCM is a semi-empirical model, the vegetation structure is not represented in detail. Instead, the $V_{1}$ and $V_{2}$ variables represent the impact of vegetation on $\sigma^{\circ}$. They can be related to the VWC or to proxies of the VWC such as LAI or vegetation indices (e.g., the normalized difference vegetation index, NDVI). In the original WCM [7] $V_{1}$ is set as $V_{1}=1$. In other studies, the same vegetation variable such as LAI or VWC is used for both $V_{1}$ and $V_{2}$ (for example $[8,24,30,32]$ ). Other authors proposed to use different variables to act as $V_{1}$ and $V_{2}$ [25,33,34].

In this study, $V_{1}$ was set as $V_{1}=1$ and LAI was used as a proxy for VWC [30]:

$$
\left\{\begin{array}{c}
V_{1}=1  \tag{7}\\
V_{2}=L A I
\end{array}\right.
$$

Preliminary tests have shown that Equation (7), corresponding to the original WCM [7], gives better results than other options over southwestern France.

The WCM (Equations (1)-(7)) contains four static parameters whose values may change from one area to another. The $A$ and $B$ parameters in Equations (4)-(5), which are dimensionless, are related to vegetation properties. There is no universal theoretical method to characterize the best group of vegetation descriptors, and thus to retrieve the values of the $A$ and $B$ parameters [25]. These parameters depend on the canopy type and on radar configuration. The $C$ and $D$ parameters in Equation (2), in dB units, are related to soil properties. Parameter $C$ is the value of the backscatter coefficient for a perfectly dry soil and is essentially controlled by the surface roughness and incidence angle. Parameter $D$ refers to the radar sensitivity to variations in soil moisture, which depends on the radar configuration and soil characteristics.

It is interesting to note that in this configuration of the WCM (Equation (7)), there is a critical value of SSM for which only one $\sigma^{\circ}$ value equal to $A \cos \theta$ can be simulated by the WCM, whatever the LAI value:

$$
\begin{equation*}
\operatorname{SSM}_{C}=\left(10 \log _{10}(A \cos \theta)-C\right) / D \tag{8}
\end{equation*}
$$

### 2.6. Model Calibration

The WCM model is a semi-empirical model and its parameter values $A, B, C$, and $D$ at given grid cell must be estimated by calibrating the model against observations. In order to avoid the impact of changes in the vegetation coverage caused by the Klaus storm in early 2009, the time period before the storm and during 2009 is not accounted for in the WCM calibration over southwestern France. Instead of the whole 2007-2016 time period, only the 2010-2016 subset is considered for calibration and validation. To assess the robustness of the calibrated WCM parameters, the $\sigma^{\circ}$ simulations of the calibrated WCM are compared with the $\sigma^{\circ}$ observations that are not used in the calibration. The calibration and the validation are performed during the 2010-2013 and 2014-2016 time periods, respectively. In order to check the stability of the retrieved parameter values, an additional calibration is performed over a longer period of time (2010-2016) encompassing the initial calibration period and the validation period.

Al-Yaari et al. [35] derived L-band VOD estimates from SMOS (Soil Moisture and Ocean Salinity) observations. Assuming that the L-band VOD is a proxy for standing biomass, they showed that the
impact of Klaus on the Landes forest biomass, including the impact of forestry work following the storm, was pronounced until the end of 2012. In this study, we investigate to what extent the Klaus event can be observed by ASCAT. In addition to the whole WCM calibration over southwestern France, a specific calibration for the storm area of the Landes forest (Figure 1) is performed for three time periods: pre-storm (January 2007 to 24 January 2009), forest degradation ( 25 January 2009 to December 2012), and forest regeneration (2013-2016).

For retrieving the values of the WCM parameters, the calibration process is done by comparing simulated and observed $\sigma^{\circ}$ values expressed in linear units. In field experiments where homogeneous land-cover conditions can be ensured, the two soil parameters ( $C$ and $D$ ) can be obtained over bare soil by a linear model fitting as expressed in Equation (2) [7]. This method cannot be used for the low-resolution ASCAT $\sigma^{\circ}$ observations from space, because the large ASCAT pixels may include various land-cover types, bare soil, and vegetated surfaces.

In this study, an approach consisting of simultaneously retrieving $A, B, C$, and $D$ is used. A cost function $K$ as expressed in Equation (9) is minimized.

$$
\begin{equation*}
K=\sqrt{\frac{1}{N} \sum_{i}^{N}\left(\sigma_{m o d}^{0}-\sigma_{o b s}^{0}\right)^{2}}+W_{\alpha} \frac{1}{N_{\alpha}} \sum_{i}^{N_{\alpha}} \frac{\left(\alpha_{0, i}-\alpha_{i}\right)^{2}}{\sigma_{\alpha_{(0, i)}}^{2}} \tag{9}
\end{equation*}
$$

In Equation (9), the cost function incorporates the backscatter coefficients predicted by the water cloud model $\left(\sigma_{m o d}^{0}\right)$ and those observed by ASCAT $\left(\sigma_{o b s}^{0}\right)$, which are all in linear units, along with a parameter penalty. The $N$ symbol represents the number of $\sigma^{\circ}$ simulations and observations, $N_{\alpha}$ represents the number of fitted $W C M$ parameters, $W_{\alpha}$ represents the weight factor given to the parameter penalty term, $\alpha_{i}$ represents the $\mathrm{i}^{\text {th }}$ parameter value, and $\alpha_{i, 0}$ represents the prior value of the $\mathrm{i}^{\text {th }}$ parameter. The minimization is performed using the Shuffled Complex Evolution Algorithm (SCE-UA) method [36]. The SCE-UA method is widely used and has proven as being robust and effective for fitting model parameters [37]. Lievens et al. [8] successfully used this technique to calibrate WCM parameters at a global scale. We use the same weight-factor value set to 0.01 as in [8]. The variance of each parameter $\sigma_{\alpha_{(0, i)}}^{2}$ is assumed to be equal to the variance of a uniform distribution as expressed in Equation (10) with boundaries $\left[\alpha_{\max , i}, \alpha_{\min , i}\right]$ set as in [38].

$$
\begin{equation*}
\sigma_{\alpha_{(0, i)}}^{2}=\frac{\left(\alpha_{\max , i}-\alpha_{\min , i}\right)^{2}}{12} \tag{10}
\end{equation*}
$$

The prior and boundaries values of the dimensionless WCM parameters are fixed as those given in Table 2 of [8].

The implementation of the model calibration is illustrated in Figure 2.


Figure 2. Flowchart of data and methods used in this study for model calibration.

### 2.7. Implementation of $\sigma^{\circ}$ Simulations

The calibrated WCM is used to produce $\sigma^{\circ}$ simulations over southwestern France from 2010 to 2016, using the SSM simulations and LAI observations described in Sections 2.2 and 2.4, respectively.

In order to remove the impact of soil-freezing conditions on the comparison with the observed ASCAT $\sigma^{\circ}$, regions presenting simulated topsoil surface temperature below $2^{\circ} \mathrm{C}$ and ice are masked out. Specific simulations are used to investigate the impact of the Klaus storm on the Landes forest by using a time series of the mean simulated $\sigma^{\circ}$ values over the North, Storm, and South zones (Figure 1) from 2007 to 2016.

### 2.8. Statistical Analysis

The WCM model results for $\sigma^{\circ}$ are compared to satellite observations measurements using the Pearson correlation coefficient $(R)$ and the RMSD. While the observed and simulated $\sigma^{\circ}$ from the WCM is expressed in linear units during the calibration process, values expressed in dB units are used for calculating the $R$ and RMSD scores.

The analysis of the impact of the Klaus storm is based on the North, Storm, and South zones in Figure 1 (Section 2.1), as defined by [13]. Following the method used by [13] to assess differences in cloud coverage between forest and non-forest areas, the difference in $\sigma^{\circ}$ between the Storm zone and the average of the North and South zones is investigated. The difference is calculated for the ASCAT observations, and for the WCM simulations.

$$
\begin{equation*}
\text { Diff } f_{\sigma^{0}}=\sigma_{\text {stormzone }}^{0}-\frac{\left(\sigma_{\text {northzone }}^{0}+\sigma_{\text {southzone }}^{0}\right)}{2} \tag{11}
\end{equation*}
$$

We used the forest $\sigma^{\circ}$ difference with neighboring areas in order to eliminate the weather factor. Preliminary tests based on a simple time series of $\sigma^{\circ}$ over the Landes forest showed that the impact of the storm was not clearly visible. The $\sigma^{\circ}$ values are sensitive to rainfall events, and the storm impact on the signal is masked by the weather factor. Using the difference with neighboring areas as in [13] tends to eliminate this factor. We do not focus on the same subject as addressed by [13], but we follow the same protocol to highlight differences in the geophysical variables.

## 3. Results

### 3.1. Parameter Values

Retrieved $A$ and $B$ vegetation parameter values range from 0.07 to 0.20 and from 0.2 to 1.7, respectively (Table 1). Figure 3 shows the probability distribution of parameter values. The large skewness score for $B$ (Table 1 ) indicates that the probability distribution of this parameter is not Gaussian. It presents a long tail toward large values. The most frequent $B$ values range from 0.3 to 0.5 . The largest $B$ values are observed close to the Mediterranean coast and over C3 crops such as wheat. The latter tend to display intermediate values of $A$ and relatively large values of $B$ ranging mainly from 0.5 to 0.8 . The statistical distribution of $A$ corresponds to rather evenly distributed values and can be related to well-known geographic patterns. Figure 4 shows that very large values of $A$ (close to 0.20 ) correspond to the wide urban areas of Toulouse and Bordeaux. Values of $A$ around 0.17 tend to match with the large fractions of broadleaf trees in Figure 1. Small values of $A$ (around 0.10 ) tend to match with the large fractions of grass and coniferous trees in Figure 1.

Regarding soil parameters $C$ and $D$, Figure 4 shows that urban areas present large values for both ( $C>-16 \mathrm{~dB}$ and $D>29 \mathrm{~dB}$ ). Meanwhile, the Landes forest presents large values of $C$ and $D$ (around -16 dB and 29 dB , respectively), the volcanoes of Cantal (landmark " 3 " in Figure 4) present very low values (around -19.5 dB and 25 dB , respectively). It must be noted that the soil types of these areas are quite different. While the Landes forest is characterized by sandy soils [12], the soils of Cantal are loamy (they are classified as Andosols in the French soil classification system [39]). Another difference between Landes and Cantal is altitude (below 150 m a.s.l. and above 900 m a.s.l., respectively) and topography (flat and complex terrain, respectively). Interestingly, low values of $C$ are also found for mountainous karstic areas: Quercy, Corbières, Cévennes (landmarks " 4 ", " 5 ", and " 6 " in Figure 4, respectively).

Table 1. Water cloud model (WCM) parameters ( $A, B, C$, and $D$ ) over southwestern France: minimum, median, and maximum values, together with standard deviation and skewness scores.

| Time period | Parameter | Median [Minimum, Maximum] | Standard deviation | Skewness |
| :---: | :---: | :---: | :---: | :---: |
| 2010-2013 <br> (calibration period) | $A$ | $0.14[0.07,0.20]$ | 0.02 | -0.51 |
|  | $B$ | $0.36[0.20,1.71]$ | 0.21 | 2.30 |
|  | $C(\mathrm{~dB})$ | $-17.9[-20.0,-15.1]$ | 0.8 | 0.10 |
| $2010-2016$ | $A$ | $27.9[24.9,29.7]$ | 0.7 | -0.66 |
|  | $B$ | $0.14[0.07,0.20]$ | 0.02 | -0.49 |
|  | $C(\mathrm{~dB})$ | $0.41[0.22,1.50]$ | 0.19 | 1.93 |
|  | $D(\mathrm{~dB})$ | $-17.6[-20.0,-14.9]$ | 0.8 | -0.04 |



Figure 3. WCM parameters: histograms of calibrated values over the 2010-2013 calibration period (in blue) and over the 2010-2016 period (in red) over southwestern France at a spatial resolution of $25 \mathrm{~km} \times 25 \mathrm{~km}$ (representing 308 grid cells).



Figure 4. WCM parameters: calibrated values for 2010-2016 over southwestern France. From left to right and from top to bottom: parameters $A, B, C$, and $D$. Areas presenting a mean elevation greater than 1200 m a.s.l. are in white. Geographic landmarks are indicated: (a) " 1 " and " 2 " for Toulouse and Bordeaux urban areas, $(\mathbf{c}, \mathbf{d})$ " 3 ", " 4 ", " 5 " and " 6 " for the volcanoes of the Cantal, and for Quercy, Corbières, Cévennes karstic areas, respectively.

Figure 3 and Table 1 also show that the $A$ parameter values resulting from the calibration over a longer period of time (2010-2016) present a statistical distribution similar to the initial parameter values calibrated over 2010-2013. The histograms of the other parameters are slightly shifted toward larger values.

### 3.2. Performance of the WCM

The performance of the calibration of the WCM using the SCE-UA algorithm is assessed in Table 2. Simulated and observed $\sigma^{\circ}$ values are compared using a large number of observations ( $n$ ) for the calibration and for the validation period, using the $R$ and RMSD scores. For these two periods of time, $n=209,327$ and $n=204,520$ observations are available, respectively, after sorting out the soil freezing events. For each time period, two data subsets are considered in addition to the pooled dataset: springtime (i.e., in March, April, and May (MAM)) and summertime (i.e., in June, July and August (JJA)). Table 2 shows that the scores for the validation period are very close to those for the calibration period. The WCM performs better in the springtime in terms of correlation than in the summertime. While the median $R$ value is 0.60 for the calibration period in the springtime, a value of 0.44 is obtained in the summertime. Negative values are even observed in the summertime. On the other hand, the RMSD score presents better values in the summertime. The mean model bias (not shown) is +0.11 dB in the springtime and -0.14 dB in the summertime. The WCM bias is further examined in Figure 5.

Table 2. WCM performance: statistical scores of simulated $\sigma^{\circ}$ values over southwestern France. The calibration period of the parameters is from 2010 to 2013, and the validation period is from 2014 to 2016. For both calibration and validation periods, scores are given for the pooled dataset (All) and for the March, April, and May (MAM) spring period and the June, July, and August (JJA) summer period. The number of observations is indicated ( $n$ ).

| Scores | $R$ Median [Minimum, Maximum] <br> (n) |  |  | RMSD in dB Median <br> [Minimum, Maximum] |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Seasons | All | MAM | JJA | All | MAM | JJA |
| Calibration (2010-2013) | $\begin{gathered} 0.67 \\ {[0.16,0.80]} \\ (209327) \end{gathered}$ | $\begin{gathered} 0.60 \\ {[0.02,0.77]} \\ (45348) \end{gathered}$ | $\begin{gathered} 0.44 \\ {[-0.18,0.71]} \\ (90082) \end{gathered}$ | $\begin{gathered} 0.35 \\ {[0.22,0.68]} \end{gathered}$ | $\begin{gathered} 0.39 \\ {[0.23,0.86]} \end{gathered}$ | $\begin{gathered} 0.32 \\ {[0.17,0.54]} \end{gathered}$ |
| Validation (2014-2016) | $\begin{gathered} 0.69 \\ {[0.17,0.82]} \\ (204520) \end{gathered}$ | $\begin{gathered} 0.60 \\ {[-0.04,0.80]} \\ (45805) \end{gathered}$ | $\begin{gathered} 0.47 \\ {[-0.38,0.68]} \\ (83139) \end{gathered}$ | $\begin{gathered} 0.36 \\ {[0.20,0.68]} \end{gathered}$ | $\begin{gathered} 0.36 \\ {[0.19,0.66]} \end{gathered}$ | $\begin{gathered} 0.32 \\ {[0.18,0.75]} \end{gathered}$ |

In Figure 5, maps of simulated $\sigma^{\circ}$ values are compared with ASCAT $\sigma^{\circ}$ observations for spring and for summer. The large urban areas of Toulouse and Bordeaux are clearly visible in Figure 5 because they present the largest observed $\sigma^{\circ}$ values. The latter correspond to the high $A$ and $C$ values observed in Figure 4. The temporal correlation between the WCM simulations and the observations is also shown. Again, this score tends to present better values in the springtime than in the summertime. Small or negative correlations are found in locations corresponding to the three karstic areas presented in Figure 4. The mean simulated $\sigma^{\circ}$ maps are quite similar to the observations (not shown), and the mean seasonal bias is generally very small. However, a seasonal bias can be observed over agricultural areas mainly covered by C 3 crops (see Figure 1). An example of such an agricultural area is Lomagne (" 7 " in Figure 5). Over these areas, the calibrated WCM tends to overestimate $\sigma^{\circ}$ in the springtime and to underestimate $\sigma^{\circ}$ in the summertime.


Figure 5. WCM performance: ( $\mathbf{a}, \mathbf{b}$ ) observed $\sigma^{\circ}$ from Advanced Scatterometer (ASCAT) (sigma0_Obs), (c,d) WCM correlation coefficient scores and (e,f) mean bias (simulations-observations), for ( $\mathbf{a}, \mathbf{c}, \mathbf{e}$ ) the March, April, and May (MAM) spring period and the June, July, and August (JJA) summer period. All values are averaged from 2010 to 2016. Areas presenting an elevation greater than 1200 m a.s.l are in white. Geographic landmarks are indicated: $(\mathbf{a}, \mathbf{b})$ " 1 " and " 2 " for the Toulouse and Bordeaux urban areas; (c,d) " 4 ", " 5 ", and " 6 " for the Quercy, Corbières, and Cévennes karstic areas, respectively; and (e,f) " 7 " and " 8 " for the Lomagne and Bas-Armagnac (South zone in Figure 1) agricultural areas, respectively.

Figure 6 presents the daily and monthly time series of spatially averaged simulated and observed $\sigma^{\circ}$ over southwestern France. It appears that the simulated ASCAT $\sigma^{\circ}$ values in the springtime are systematically higher than the observed ones. The $\sigma^{\circ}$ observations are often lower in the springtime than in the summertime. This seasonal bias is consistent with the biases observed in Figure 5 over the C3 crop areas. In spite of the seasonal mismatch between observed and simulated values, the monthly time series of scaled anomaly in Figure 6 show that the simulated month-to-month variability of $\sigma^{\circ}$ is consistent with the observations.


Figure 6. WCM performance: $\sigma^{\circ}$ simulated by the WCM (red lines and dots) vs. ASCAT $\sigma^{\circ}$ observations (blue lines and dots) and over southwestern France from 2010 to 2016. (a) Daily and (b) monthly mean values. (c) Scaled monthly anomalies.

### 3.3. Landes Forest: Impact of the Klaus Storm

The result of the analysis method consisting of comparing the Storm area (Figure 1) with the bordering North and South agricultural areas (see Section 2.8) is presented in Figure 7. It is observed that the seasonal cycle of the monthly difference in $\sigma^{\circ}$ observations changes after the storm event of 24 January 2019. Before this date, the difference is small in the springtime ( $>-0.8 \mathrm{~dB}$ ) and large in the autumn and wintertime $(<-1.0 \mathrm{~dB})$. After this date, the ASCAT $\sigma^{\circ}$ seasonal cycle that was present before is no longer noticed up until the end of 2012. The pre-storm pattern starts reappearing in 2013. In order to assess the ability of the WCM to represent this behavior, the four parameters of the WCM were calibrated for the Storm area for three distinct time periods indicated in Figure 7: pre-storm, forest degradation, and forest regeneration (2013-2016). Table 3 shows the values of the WCM parameters obtained for each time period over the Storm area.


Figure 7. Landes forest Storm area: differences in $\sigma^{\circ}$ and leaf area index (LAI) with respect to bordering agricultural areas. (a) ASCAT $\sigma^{\circ}$ observations (blue line), (b) simulated $\sigma^{\circ}$ values using the WCM parameters values listed in Table 3 (red line) vs. observations (blue line), (c) LAI.

Table 3. Landes forest Storm area: parameters of the WCM before and after the Klaus storm event of 24 January 2009. The number of observations is indicated $(n)$. The contrasting value of $B$ for the forest regeneration period is in bold.

| Time Period | WCM Parameters |  |  |  |  | Scores |  |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | $\boldsymbol{A}$ | $\boldsymbol{B}$ | $\boldsymbol{C}$ |  |  |  |  |
| $(-)$ | $\boldsymbol{C}$ |  |  |  |  |  |  |
| (in dB) | (in dB) | $\boldsymbol{R}(\boldsymbol{n})$ | RMSD <br> (in dB) |  |  |  |  |
| Pre-storm (January 2007 to January 2009) | 0.13 | 0.19 | -16.5 | 27.3 | $0.74(503)$ | 0.33 |  |
| Forest degradation (February 2009 to December 2012) | 0.13 | 0.20 | -16.5 | 27.3 | $0.79(1027)$ | 0.42 |  |
| Forest regeneration (January 2013 to December 2016) | 0.12 | $\mathbf{0 . 2 9}$ | -16.5 | 27.9 | $0.80(1203)$ | 0.40 |  |

Overall, the obtained WCM parameter values do not change much from one time period to another, except for $B$. The $B$ value corresponding to the forest regeneration period $(B=0.29)$ is much larger than for the pre-storm and forest degradation time periods ( $B \approx 0.20$ ). This corresponds to an increase of $45 \%$ in VOD value for a given value of LAI during the regeneration period. The monthly difference in $\sigma^{\circ}$ simulated by the WCM according to the parameter values listed in Table 3 are compared with the observations in Figure 7.

In addition to $\sigma^{\circ}$ differences, Figure 7 shows differences in LAI of the Storm area with respect to bordering agricultural areas. The main discontinuity in this time series corresponds to the storm. It consists of a reduction of the LAI difference annual cycle after the storm. This change in LAI difference is entirely due to a discontinuity in the LAI of the Storm area after the storm event. Before the storm,
the LAI of the pine forest presents a marked annual cycle and ranges from $1.2 \mathrm{~m}^{2} \mathrm{~m}^{-2}$ in the wintertime to $4.5 \mathrm{~m}^{2} \mathrm{~m}^{-2}$ in the summertime (Figure 8). After the storm, the amplitude of the LAI annual cycle is reduced. The annual maximum LAI of the degraded forest does not exceed $3.5 \mathrm{~m}^{2} \mathrm{~m}^{-2}$, and the annual minimum LAI presents smaller values than before the storm, ranging from 0.5 to $1.0 \mathrm{~m}^{2} \mathrm{~m}^{-2}$. Since the WCM parameters do not change much from the pre-storm period to the forest degradation period (Table 3), this result confirms that the ability of the WCM to simulate changes in $\sigma^{\circ}$ differences during the forest degradation period comes from the LAI forcing. On the other hand, the main driver of changes in $\sigma^{\circ}$ differences during the forest regeneration period is the increase in $B$ value.


Figure 8. Mean monthly Copernicus Global Land Service (CGLS) LAI observations over the Landes forest area most affected by the Klaus storm before (2007) and after (2009) the storm (purple and green lines, respectively).

## 4. Discussion

### 4.1. Is the WCM Able to Represent Vegetation Effects?

In Section 3.3, it is shown that the WCM is able to simulate the behavior of the $\sigma^{\circ}$ observed over the Landes pine forest before the Klaus storm. The WCM performs well just after the storm, provided that LAI observations can be integrated into the model. The $B$ parameter value does not change at this time, and the impact of the storm on the forest $\sigma^{\circ}$ values is determined by smaller LAI values (Figure 8). Actually, this area remained a forested area but with much fewer standing trees after the storm. On the other hand, increasing the $B$ parameter value by $45 \%$ (see Table 3 ) is needed to accurately simulate the transition from the forest degradation period to the regeneration period. This could be related to a drastic change in the tree age distribution, with much more young trees.

Over agricultural areas where C 3 crops such as wheat are dominant (e.g., the Lomagne), Figure 5 shows that the simulated $\sigma^{\circ}$ values are higher than the observed values in the springtime. This seasonal bias is also visible in Figure 6. In spite of this bias, Figure 6c shows that the simulated month-to-month anomaly variability of $\sigma^{\circ}$ is able to capture the extreme spring drought that was observed in 2011 [40]. Figure 4 shows that the $C 3$ crop area presents relatively large values of the $B$ parameter. The parameters of the WCM are listed in Table 4 for Lomagne and for Bas-Armagnac. The $B$ parameter value is larger for Lomagne than for Bas-Armagnac ( 0.51 and 0.34 , respectively). For a given value of LAI, this means that the sensitivity of the simulated $\sigma^{\circ}$ to SSM is much smaller for Lomagne than for Bas-Armagnac. The large value of the $B$ vegetation parameter over Lomagne may also be the signature of missing processes in the WCM in the springtime, such as for example (1) multiple scattering within the vegetation canopy of specific crop types or (2) changes in soil roughness caused by agricultural practices (e.g., tillage). Another explanation could be that $B$ presents a seasonal cycle. A specific WCM calibration performed for the springtime season (MAM only) is shown in Table 4. The most noticeable change in parameter values is the greatly reduced value of $B(B=0.28$ instead of 0.51$)$. This result suggests that a misrepresentation of scattering within the vegetation canopy in relation to the rapid physiological changes of the wheat crop may contribute to the model bias.

Table 4. Agricultural areas: parameters of the WCM for Lomagne and Bas-Armagnac (" 7 " and " 8 " in Figure 5, respectively). The number of observations is indicated ( $n$ ). The contrasting value of $B$ for Lomagne at springtime is in bold.

| Agricultural Areas | WCM Parameters |  |  |  | Scores |  |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: |
|  | $A$ <br> $(-)$ | $\boldsymbol{B}$ <br> $(-)$ | $\boldsymbol{C}$ <br> (in dB) | $\boldsymbol{D}$ <br> (in dB) | $\boldsymbol{R}(\boldsymbol{n})$ | RMSD <br> (in dB) |
|  | 0.13 | $\mathbf{0 . 5 1}$ | -16.9 | 27.7 | $0.74(1954)$ | 0.65 |
|  | 0.11 | 0.28 | -18.3 | 29.0 | $0.77(499)$ | 0.54 |
| Bas-Armagnac | 0.14 | 0.34 | -17.9 | 27.5 | $0.77(2669)$ | 0.38 |

In order to understand the specific behavior of agricultural areas such as Lomagne with respect to Bas-Armagnac, Figure 8 presents a comparison of the observed and simulated response of $\sigma^{\circ}$ to SSM and to LAI. Over Bas-Armagnac, the WCM predicts higher $\sigma^{\circ}$ values in dry conditions for large vegetation coverage ( $\mathrm{LAI}>2.2 \mathrm{~m}^{2} \mathrm{~m}^{-2}$ ) than for sparse vegetation ( $\mathrm{LAI}<1.0 \mathrm{~m}^{2} \mathrm{~m}^{-2}$ ). The reverse result is obtained in wet conditions for SSM values larger than $S S M_{C}=0.30 \mathrm{~m}^{3} \mathrm{~m}^{-3}$ (Equation (8)). We performed a statistical test in order to evaluate to what extent this behavior is present in the observations. In dry conditions, it was found that the observed $\sigma^{\circ}$ values for the large LAI class (LAI $>2.2 \mathrm{~m}^{2} \mathrm{~m}^{-2}$ ) are significantly higher ( p -value $<0.01$ ) than those corresponding to sparse vegetation ( $\mathrm{LAI}<1 \mathrm{~m}^{2} \mathrm{~m}^{-2}$ ) and intermediate LAI values ranging from 1 to $2.2 \mathrm{~m}^{2} \mathrm{~m}^{-2}$. On the other hand, the observed $\sigma^{\circ}$ corresponding to small LAI values are not significantly different from those corresponding to intermediate LAI values. In wet conditions, the observed $\sigma^{\circ}$ corresponding to large LAI values are significantly lower than those corresponding to sparse vegetation, but they are not significantly different from those corresponding to intermediate LAI values. Over Lomagne, Figure 9 shows that $\sigma^{\circ}$ observations for large vegetation coverage ( $\mathrm{LAI}>1.7 \mathrm{~m}^{2} \mathrm{~m}^{-2}$ ) behave differently from the Bas-Armagnac ones, especially in dry conditions. While dense vegetation tends to trigger high $\sigma^{\circ}$ values in dry conditions over Bas-Armagnac, very low $\sigma^{\circ}$ values ( $<-11 \mathrm{~dB}$ ) can be observed over Lomagne in similar conditions. The WCM succeeds in predicting the observed relatively low $\sigma^{\circ}$ values of sparse vegetation ( $\mathrm{LAI}<0.5 \mathrm{~m}^{2} \mathrm{~m}^{-2}$ ) in dry conditions (for SSM values smaller than $\mathrm{SSM}_{\mathrm{C}}=0.25 \mathrm{~m}^{3} \mathrm{~m}^{-3}$ ), and vice versa in wet conditions (high $\sigma^{\circ}$ values are observed for sparse vegetation). On the other hand, the WCM is not able to predict the very low values of $\sigma^{\circ}$ observed in dry and moderately dry conditions in large vegetation coverage conditions.

Figure 10 presents LAI time series for the two agricultural areas of Bas-Armagnac and Lomagne. It appears that the two crop growth cycles are completely different. While LAI generally peaks only once per year in the springtime over Lomagne, two marked peaks are observed over Bas-Armagnac. In general, the most pronounced peak occurs in the summertime over Bas-Armagnac, following a first peak occurring at springtime. This rather complex vegetation growth cycle results from the crop rotation system and from the sub-grid heterogeneity of crop types. Figure 1 shows that in Bas-Armagnac, the maize summer crop is dominant. This can explain the large LAI peak observed in the summertime over this area. Figure 10 also shows that the largest LAI values over Lomagne (LAI $>1.7 \mathrm{~m}^{2} \mathrm{~m}^{-2}$ ) systematically occur in the springtime. This means that the lowest values of the observed $\sigma^{\circ}$ in Figure 9 for Lomagne correspond to the springtime LAI peak. The WCM is not able to represent $\sigma^{\circ}$ during the springtime LAI peak over Lomagne. The more pronounced LAI peak observed in the springtime for Lomagne suggests that winter crops are more frequent over Lomagne than over Bas-Armagnac. This would imply that the vegetation fractional coverage is larger in the springtime over Lomagne (i.e., that the fraction of bare soil is smaller) than over Bas-Armagnac. In addition, winter and summer crops often consist of wheat in this area [41]. Contrary to maize, a well-developed wheat crop can be completely opaque at the C -band for the VV polarization [42], preventing the use of $\sigma^{\circ}$ for soil moisture retrieval. Picard et al. [43] showed that $\mathrm{VV} \sigma^{\circ}$ observations at an incidence angle of $40^{\circ}$ (close to the configuration of the ASCAT observations used in this study) are affected by
large changes in the ratio of vegetation to soil contribution to backscatter. At the beginning of the spring, soil backscatter is the dominant mechanism. The stem-ground interaction gradually becomes the dominant mechanism, and soil moisture has no longer an impact on the signal. Fieuzal et al. [41] have shown in a case study over southwestern France that the $\sigma^{\circ}$ values at C-band decreases to low values over wheat fields during the stem elongation phase, while NDVI (a proxy for LAI) increases to reach its peak value, even when no major change in SSM is observed. Since the wheat LAI peaks at the end of the stem elongation phase, this can explain the low $\sigma^{\circ}$ values observed over Lomagne in the springtime.


Figure 9. Agricultural areas: $\sigma^{\circ}$ response to surface soil moisture (SSM) and LAI variables. (a,c) observed ASCAT $\sigma^{\circ}$, (b,d) simulated $\sigma^{\circ}$, (a,b) Bas-Armagnac ("South" in Figure 1) and (c,d) Lomagne agricultural areas. LAI $0 \%-20 \%, 21 \%-79 \%, 80 \%-100 \%$ percentile classes are indicated (red dots, blue triangles, and green stars, respectively).


Figure 10. Agricultural areas: observed satellite-derived GEOV2 LAI values from 2010 to 2016 over Bas-Armagnac ("South" in Figure 1) and Lomagne.

### 4.2. Can the WCM be Improved?

Thanks to a seasonal analysis of the model scores, this study shows that the WCM presents seasonal biases over agricultural areas comprising a large fraction of wheat fields. The low values of $\sigma^{\circ}$ observed at springtime over these areas could be better represented by using a specific calibration of the WCM for this period of the crop growth cycle.

Tables 3 and 4 show that the $B$ vegetation parameter of the WCM may change through time, with a larger $B$ value during the Landes forest regeneration and a smaller $B$ value in the springtime for the wheat areas of Lomagne, respectively. The former could be explained by the fact that the young trees of the pine forest stands of the Landes forest do not completely cover the soil surface, and that the biomass of understory vegetation is not completely developed yet [44]. The latter could at least partly be explained by the rising values of the specific leaf area (SLA) of wheat during the stem elongation phase [45]. Since for low vegetation, VOD is probably more related to the standing biomass than to LAI at C-band, an inverse relationship between $B$ and SLA is to be expected.

In addition, we found that karstic areas are not easily simulated by the WCM over southwestern France. As a result, small and even negative correlations between observed and simulated $\sigma^{\circ}$ values are observed over these areas (Figure 5). In order to improve the genericity of the observation operator, the analysis performed in this study should be extended to a global scale. This would permit constraining model errors in various conditions of the soil-plant system. For example, negative correlations between ASCAT SSM retrievals and independent estimates of SSM have been observed over some arid areas [46]. In addition, it is likely that other crop-rotation systems or other forest types such as tropical forests can be challenging for the WCM.

### 4.3. Can the WCM Be Used as an Observation Operator?

The results of this study show that the WCM could be used as an observation operator for the assimilation of ASCAT $\sigma^{\circ}$ observations into the ISBA LSM provided that larger model errors over karstic areas and over wheat croplands in the springtime are accounted for. It is also shown that integrating LAI observations into the WCM is needed to account for extreme events (e.g., the Klaus storm in January 2009) and to quantify the model error (e.g., larger model errors during the spring LAI peak of wheat). More often than not, the LAI information is particularly useful in very dry or very wet conditions, because the WCM predicts little influence of the LAI on $\sigma^{\circ}$ for intermediate SSM values. The LDAS-Monde tool is able to jointly assimilate LAI and SSM observations in the ISBA land surface model. Since the data flow within LDAS-Monde already includes LAI [47], analyzed LAI values could be used to force the WCM in order to analyze soil moisture. In this case, the ASCAT Level $1 \sigma^{\circ}$ observations would be used instead of the Level 2 SSM product.

The WCM seasonal biases over wheat should be taken into account in the assimilation of $\sigma^{\circ}$ observations. One way could be to allow seasonal changes in the WCM parameters (e.g., the $B$ parameter as discussed in Section 4.2). Seasonal B retrievals could be informative and allow the monitoring of SLA, which is a key land surface model variable. This seasonal retrieval could also be refined by estimating the $B$ parameter via data assimilation, but it would raise the question of cross-covariances between $B$ and the variables LAI and SSM. Another option would be to remove seasonal biases by adjusting the probability density function of the observations to the model's one, or to assimilate scaled anomalies (see Figure 6c). These seasonal biases could also be estimated. Biases can either come from ISBA model deficiencies (e.g., ISBA not being able to simulate an adequate LAI and SSM over a certain area), or deficiencies from the WCM, thus introducing a bias between observed and simulated $\sigma^{\circ}$. Both model and observation biases can be estimated through data assimilation (see e.g., Ménard [48] and references therein). LDAS-Monde could be adapted to this context and would provide precious information on the source of bias. Assimilating $\sigma^{\circ}$ in a LDAS also raises the question of how to specify observation, background, and model error covariance matrices. The last decade has seen the development of techniques to estimate those matrices. Approaches based on

Desroziers diagnostics [49] are affordable for LDASs from a computational point of view and could provide insightful information on the various sources of the data assimilation system.

Finally, part of the difficulty in simulating the ASCAT $\sigma^{\circ}$ values is related to the low spatial resolution of this sensor. This is particularly true for agricultural areas presenting a large diversity of crop types. Using disaggregated ASCAT $\sigma^{\circ}$ values or high resolution $\sigma^{\circ}$ values such as those observed by the Sentinel-1 satellites [50] together with vegetation products derived from Sentinel-2 satellites [51] could be a way to go forward.

### 4.4. Are Satellite-Derived LAI Values Reliable?

Our results show that the CGLS satellite-derived LAI product can be used to calibrate and operate the WCM. This LAI product has many advantages. It does not present the unrealistic large variations observed in products such as MODIS Collection 4 (e.g. [11]) and Collection 5 (e.g. [52,53]). In addition, the CGLS product is less prone to saturation effects than MODIS and compares much better to reference LAI maps containing ground observations [53]. Yan et al. [54] showed that the quality of the MODIS Collection 6 product is better than for Collection 5 and that the direct validation scores with respect to in situ LAI observations get closer to those given by [19] for the CGLS product.

The satellite-derived LAI values for the unperturbed forest are consistent with typical values observed over the Landes forest. Using in situ observations over a mature (30 years) forest stand of the Landes forest, Rivalland et al. [55] showed that the total LAI can vary from $1.8 \mathrm{~m}^{2} \mathrm{~m}^{-2}$ in February to $4.2 \mathrm{~m}^{2} \mathrm{~m}^{-2}$ at the end of July (Figure 1a in [55]). They also showed that a key driver of the LAI seasonal cycle is the understory vegetation, which has no green leaves in the wintertime and has a LAI of about $1.5 \mathrm{~m}^{2} \mathrm{~m}^{-2}$ in July. This large contribution of the understory to the total LAI is not always observed in coniferous forests. For example, [52] showed that the maximum LAI of the understory vegetation of a coniferous forest in southern Finland ranges from 0.2 to $0.8 \mathrm{~m}^{2} \mathrm{~m}^{-2}$. This could explain why they observed small seasonal variations of total LAI based on field measurements. Figure 8 shows that the CGLS LAI observed in 2007 over the Landes forest is consistent with the in situ observations of total LAI shown in [55]. The smaller wintertime values observed in the satellite-derived LAI before the storm ( $1.2 \mathrm{~m}^{2} \mathrm{~m}^{-2}$ against $1.8 \mathrm{~m}^{2} \mathrm{~m}^{-2}$ in [55]) could be explained by the fact that not all the forest stands in a $1 \mathrm{~km} \times 1 \mathrm{~km}$ pixel are mature.

## 5. Conclusions

In this study, C-band VV $\sigma^{\circ}$ observations over southwestern France observed by the ASCAT sensor at an incidence angle of $40^{\circ}$ are used to calibrate the WCM. Ancillary information needed to operate the WCM consists of LAI observations from the Copernicus Global Land Service and from surface soil moisture simulations of the ISBA land surface model. It is shown that the SCE-UA method for model calibration is able to produce robust estimates of the four parameters of the WCM, with validation scores values very close to the calibration ones. The WCM parameter maps are compared with well-known geographic patterns. For example, the $A$ parameter corresponding to the maximum asymptotic backscatter from elements standing over the soil surface presents larger values over large urban areas (Toulouse and Bordeaux). The $C$ parameter corresponding to the minimum soil backscatter in dry conditions presents high values over urban areas and low values over mountainous areas such as the volcanoes of Cantal and the karstic areas of Quercy, Corbières, and Cévennes. The $D$ parameter corresponding to the sensitivity of $\sigma^{\circ}$ to SSM presents very low values over the volcanoes of Cantal. The overall performance of the WCM is good, with $R$ and RMSD values of 0.7 and 0.36 dB , respectively. However, small and even negative $R$ values are observed over karstic areas, especially in dry conditions in the summertime. The bias is generally very small, except for croplands dominated by wheat in the springtime, during the stem elongation phase of the wheat. Finally, it is shown that the WCM is able to make a reasonably accurate representation of the impact of the Klaus storm on the Landes forest in January 2009. The changes in the $\sigma^{\circ}$ seasonal cycle after the storm are mainly explained by the reduced LAI values. On the other hand, changes associated with the forest regeneration phase
starting in 2013 can only be explained by an increase of the $B$ parameter corresponding to the ratio of VOD to LAI. This study focuses on methods applicable at a global scale. A more detailed analysis of LAI observations over the Landes forest could be done in a future study. More generally, focusing on higher spatial resolution products such as Sentinel- $1 \sigma^{\circ}$ data could help linking changes in WCM parameters to land-cover changes. The Sentinel- $1 \sigma^{\circ}$ data would need to be aggregated to the spatial resolution of existing global land-cover maps (e.g. $300 \mathrm{~m} \times 300 \mathrm{~m}$ ), together with satellite-derived LAI at the same spatial resolution.

Finally, more research is needed to implement the WCM as an observation operator in a LDAS.
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## Abbreviations

The following abbreviations are used in this manuscript:

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ASCAT Advanced Scatterometer
CNRM Centre National de Recherches Météorologiques
CGLS Copernicus Global Land Service
ECMWF European Centre for Medium-Range Weather Forecasts
ERA-5 ECMWF Reanalysis 5th generation
ISBA Interactions between Soil, Biosphere, and Atmosphere
JAA June-July-August
LAI Leaf Area Index
LDAS Land Data Assimilation System
LSM Land Surface Model
MAM March-April-May
MODIS Moderate Resolution Imaging Spectroradiometer
NDVI Normalized Difference Vegetation Index
PROBA-V Project for On-Board Autonomy-Vegetation
RMSD Root Mean Square Deviation
SCE-UA Shuffled Complex Evolution Algorithm
SLA Specific Leaf Area
SMOS Soil Moisture and Ocean Salinity
SPOT-VGT Vegetation sensor on SPOT ('Systeme probatoire d'observation de la Terre' or 'Satellite pour l'observation de la Terre') satellite
SSM
SURFEX Surface Externalisée (externalized surface models)
VOD Vegetation Optical Depth
VWC Vegetation Water Content
WCM Water Cloud Model
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A detailed description of the WCM (see section 4 of Chapter II) shows that the WCM model can be fitted using different vegetation descriptors. In this study, leaf area index (LAI) CGLS observations were used as a vegetation descriptor. An attempt was also made to use LAI simulated by the ISBA model over southwestern France.
The time series on Figure III. 14 show the seasonal and inter-annual variability of the two LAI products over an agricultural area and a forest area in southwestern France (the South zone and the Storm zone in Fig. 1 of Shamambo et al. (2019), respectively) from 2007 to 2016.


Figure III. 14 - Time-series showing LAI observations from the CGLS CGLS satellitederived product (in green) and the modelled LAI from the ISBA LSM (in yellow) over (top) the agricultural South zone and (bottom) the Landes forest Storm zone described in Shamambo et al. (2019).

Over the South zone, the LAI simulated by ISBA model (noted as LAI_Model in yellow) tends to present larger values over spring and summertime than LAI observations from the CGLS product (noted as LAI_OBS in green). This means that the ISBA model overestimates the simulated values of LAI over the south zone during the plant growth season. The current version of the ISBA model does not include a representation of agricultural practices (e.g. sowing, harvest) and is not able to represent crop rotation. Crop rotation is visible in the observations with a first LAI peak corresponding to winter crops and a second one corresponding to summer crops.

Over the Storm zone, the model tends to underestimate annual peak LAI values before the storm. After the storm, the model tends to overestimate LAI values during the dormant winter season. It must be noticed that the impact of the storm event on the forest is not accounted for in ISBA model simulations.

Using the modelled LAI when fitting the WCM would produce less realistic values of the WCM parameters, especially of the B parameter over agricultural areas. The use of the modelled LAI is investigated further over the Landes forest Storm zone in the next section.

### 2.3 Could other versions of the WCM be used?

In order to estimate which configuration of the WCM model performs better in simulating the radar backscatter coefficient $\left(\sigma^{\circ}\right)$, several configurations of the WCM were investigated over the forest Storm zone.
These configurations concerned

- the $V_{1}$ vegetation descriptor in the WCM (Eq. II.7),
- WCM Option 1 uses 1 as the value for $V_{1}$ and LAI values as $V_{2}$ descriptor
- WCM Option 2 uses both LAI values as $V_{1}$ and $V_{2}$ vegetation descriptors.
- the prescribed LAI product (section 2.2),
- satellite-derived (CGLS)
- modelled by the ISBA LSM
- the WCM calibration time period
- Experiment 1 consisted of fitting the WCM model parameters all at once for the combined time phase from 2007-2016 over each zone involved.,
- Experiment 2 on the other hand, involved fitting the storm zone for three distinct time periods indicated in Figure 7 of Shamambo et al. (2019): prestorm (2007-2008), forest degradation (2009-2012), and forest regeneration (2013-2016).

Option 1 was used by Shamambo et al. (2019) together with satellite derived LAI observations and Experiment 2. Tables III. 3 and III. 4 show that the configuration used in Shamambo et al. (2019) presents the best results.

When Option 1 is implemented, the results in Table III. 3 show that the Experiment 2 calibration method outperforms Experiment 1 whatever LAI product (CGLS or ISBA) is used. Furthermore, statistical scores show that when CGLS LAI is used as the vegetation descriptor for the Option 1 approach, better results are obtained ( $R=0.63$, against 0.40 for

Experiment 1). Using LAI from ISBA gives $R$ values of 0.55 and 0.30 for Experiment 2 and Experiment 1, respectively.

Using Option 2 (Table III.4), Experiment 2 with observed LAI give the best results, as for Option 1. However, the Option 2 scores are much poorer ( $R$ is decreased by 14 \% and RMSD is increased by $66 \%$ ). Option 1 largely outperforms Option 2 for both Experiment 1 and Experiment 2. Furthermore, it is confirmed that calibration of the WCM must be performed in three distinct time periods (Experiment 2) when considering the forest zone affected by the Klaus storm as this improves the WCM simulations. A different result is found when the ISBA LAI is used (Table III.4) because the storm event is not accounted for in ISBA LAI simulations.

Table III. 3 - WCM option $1\left(\mathrm{~V}_{1}=1\right)$ : Statistical scores for radar backscatter coefficient over the storm zone for the 2007-2016 time period.

| LAI forcing | Calibration | Correlation coefficient | RMSD <br> $(\mathrm{dB})$ | SDD <br> $(\mathrm{dB})$ |
| :--- | :--- | :---: | :---: | :---: |
| Observed CGLS | Experiment 1 | 0.40 | 0.182 | 0.182 |
|  | Experiment 2 | 0.63 | 0.149 | 0.149 |
| From ISBA | Experiment 1 | 0.30 | 0.186 | 0.186 |
|  | Experiment 2 | 0.55 | 0.159 | 0.159 |

Table III. 4 - WCM option 2 ( $\left.\mathrm{V}_{1}=\mathrm{LAI}\right)$ : Statistical scores for radar backscatter coefficient over the storm zone for the 2007-2016 time period.

| LAI forcing | Calibration | Correlation coefficient | RMSD <br> $(\mathrm{dB})$ | SDD <br> $(\mathrm{dB})$ |
| :--- | :--- | :---: | :---: | :---: |
| Observed CGLS | Experiment 1 | 0.42 | 0.290 | 0.286 |
|  | Experiment 2 | 0.54 | 0.248 | 0.246 |
| From ISBA | Experiment 1 | -0.07 | 0.287 | 0.286 |
|  | Experiment 2 | 0.18 | 0.293 | 0.291 |

### 2.4 Could other WCM calibration approaches be used?

The WCM parameter values $A, B, C$, and $D$ at a given grid cell are calculated by calibrating the model against observations. There are many ways of calibrating the four parameters of the WCM models. Under this section, four approaches are evaluated.

- Approach 1 comprises of calibration $A, B, C$, and $D$ parameters all at once. This approach was used in the above Sections 1 and 2.1.
- Approach 2 involves calibrating $C$ and $D$ soil parameters first for low LAI values then fitting $A$ and $B$ vegetation parameters using the whole dataset.
- Approach 3 includes fitting soil parameter $C$ first with low LAI values thereafter fitting $A, B$ and $D$ using the whole dataset.
- Approach 4 considers fitting soil parameter $D$ first with low LAI values and thereafter fitting $\mathrm{A}, \mathrm{B}$ and C using the whole dataset.

Analysis under this section is carried out over the whole southwestern France area (Figure III.13). Only the time period from 2010 to 2016 is considered in order to avoid the assessment biases that the impact of Klaus storm might bring if the period before were taken into account. In order to review the sturdiness of the calibrated WCM parameters, the $\sigma^{\circ}$ simulations of the calibrated WCM are compared with the $\sigma^{\circ}$ observations that are not used in the calibration. Three conditions are taken into account (All, Dry and Wet) under the calibration and validation processes performed during 2010-2013 and 2014-2016 time periods, respectively. The dry conditions are representative of areas with SSM values smaller than the median SSM value and wet conditions account for areas with SSM values larger than the median SSM value. The All conditions comprises both the Dry and Wet conditions. The analysis was carried out using the two versions of the WCM (Option 1 and Option 2) in order to evaluate the outcome of each approach.

Table III. 5 shows the outcome of using the WCM Option 1 method for each model calibration approach. For each approach considered, the validation scores values are very close to the calibration ones. This shows the robustness of calibrating the WCM using the SCE-UA optimization method. A closer review of each approach technique shows slightly higher correlation values and lower RMSD, and SDD values for Approach 1 and Approach 4 under each condition involved (All, Dry and Wet) than using Approach 2 and Approach 3. However, when we consider the statistical distribution of the parameters on Figure III. 15 and Figure III.18, representative of Approach 1 and Approach 4, respectively, we notice that the $D$ parameter which is proportionate to the sensitivity of $\sigma^{\circ}$ to SSM presents a Gaussian distribution on Figure III. 15 whilst histogram graph on Figure III. 18 tends to have values of $D$ which lie on the limit towards values around 15 dB . Moreover, the histogram of $D$ values during the validation time period differs from the calibrated one. The results on Figure III. 18 show that Approach 4 is less efficient when retrieving WCM parameters when compared to Approach 1. Regarding Approach 2 and Approach 3 (Figure III. 16 and Figure III.17, respectively) issues similar as for Approach 4 can be observed.

Analysis was also made for each approach using the WCM Option 2. Table III.6 shows the outcome of the statistical scores for each approach involved. For each approach considered, we see that the scores for the validation period are not as good as for the calibration period. Approach 1 has better scores for each condition considered when compared to the other approaches. Overall, the obtained scores are not as good as when Option 1 is used (Table III.5). This confirms that Option 1 should be used.

Table III. 5 - WCM Option $1\left(V_{1}=1\right)$ : Statistical scores from each methodology of calibrating the WCM over southwestern France. The calibration period of the parameters was taken from 2010 to 2013 and validation period was from 2014 to 2016. The parameters used for the Dry and Wet conditions are the same as those coming from the calibration under All conditions.

| Parameter calibration approaches WCM Option 1 ( $V_{1}=1$ ) | Time period | Correlation coefficient |  |  | RMSD <br> (dB) |  |  | SDD <br> (dB) |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Conditions |  | All | Dry | Wet | All | Dry | Wet | All | Dry | Wet |
| Number of observations | Calibration | 804 | 402 | 402 | 804 | 402 | 402 | 804 | 402 | 402 |
|  | Validation | 702 | 351 | 351 | 702 | 351 | 351 | 702 | 351 | 351 |
| Fitting $A, B, C$ and $D$ all at once | Calibration | 0.87 | 0.88 | 0.83 | 0.38 | 0.33 | 0.41 | 0.38 | 0.33 | 0.40 |
|  |  |  |  |  |  |  |  |  |  |  |
|  | Validation | 0.88 | 0.87 | 0.85 | 0.38 | 0.36 | 0.40 | 0.36 | 0.34 | 0.38 |
| $C$ and $D$ fitted first for low LAI values $A$ and $B$ then fitted using the whole dataset | Calibration | 0.86 | 0.88 | 0.83 | 0.39 | 0.33 | 0.41 | 0.39 | 0.33 | 0.41 |
|  |  |  |  |  |  |  |  |  |  |  |
|  | Validation | 0.86 | 0.86 | 0.84 | 0.40 | 0.40 | 0.41 | 0.38 | 0.37 | 0.40 |
| C fitted first for low LAI values $A, B$ and $D$ then fitted using the whole dataset | Calibration | 0.86 | 0.86 | 0.83 | 0.39 | 0.35 | 0.41 | 0.39 | 0.35 | 0.41 |
|  |  |  |  |  |  |  |  |  |  |  |
|  | Validation | 0.87 | 0.88 | 0.85 | 0.38 | 0.34 | 0.42 | 0.36 | 0.33 | 0.39 |
| Approach 4: <br> $D$ is fitted first for low LAI values $A, B$ and $C$ then fitted using the whole dataset | Calibration | 0.87 | 0.88 | 0.84 | 0.37 | 0.33 | 0.39 | 0.37 | 0.33 | 0.39 |
|  |  |  |  |  |  |  |  |  |  |  |
|  | Validation | 0.88 | 0.87 | 0.86 | 0.38 | 0.37 | 0.39 | 0.36 | 0.34 | 0.38 |

Table III. 6 - WCM Option 2 ( $\mathrm{V}_{1}=\mathrm{LAI}$ ): Stastistical scores from each methodology of calibrating the WCM over southwestern France. The calibration period of the parameters was taken from 2010 to 2013 and validation period was from 2014 to 2016. The parameters used for the Dry and Wet conditions are the same as those coming from calibration period of All conditions calibration phase.

| Parameter calibration approaches WCM Option 2 ( $V_{1}=\mathrm{LAI}$ ) | Time period | Correlation coefficient |  |  | RMSD <br> (dB) |  |  | $\begin{aligned} & \text { SDD } \\ & (\mathrm{dB}) \end{aligned}$ |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Conditions |  | All | Dry | Wet | All | Dry | Wet | All | Dry | Wet |
| Number of observations | Calibration | 804 | 402 | 402 | 804 | 402 | 402 | 804 | 402 | 402 |
|  | Validation | 702 | 351 | 351 | 702 | 351 | 351 | 702 | 351 | 351 |
| Fitting $A, B, C$ and $D$ all at once | Calibration | 0.76 | 0.77 | 0.80 | 0.62 | 0.52 | 0.47 | 0.60 | 0.50 | 0.46 |
|  |  |  |  |  |  |  |  |  |  |  |
|  | Validation | 0.72 | 0.66 | 0.76 | 0.70 | 0.85 | 0.51 | 0.66 | 0.69 | 0.50 |
| $C$ and $D$ fitted first for low LAI values $A$ and $B$ then fitted using the whole dataset | Calibration | 0.65 | 0.65 | 0.76 | 0.92 | 0.87 | 0.52 | 0.85 | 0.75 | 0.51 |
|  |  |  |  |  |  |  |  |  |  |  |
|  | Validation | 0.60 | 0.55 | 0.58 | 1.03 | 1.30 | 0.70 | 0.94 | 0.93 | 0.70 |
| C fitted first for low LAI values $A, B$ and $D$ then fitted using the whole dataset | Calibration | 0.68 | 0.69 | 0.77 | 0.83 | 0.70 | 0.50 | 0.79 | 0.65 | 0.50 |
|  |  |  |  |  |  |  |  |  |  |  |
|  | Validation | 0.62 | 0.55 | 0.65 | 0.96 | 1.19 | 0.64 | 0.90 | 0.96 | 0.64 |
| Approach 4: <br> D is fitted first for low <br> LAI values <br> $A, B$ and $C$ then fitted using the whole dataset | Calibration | 0.73 | 0.76 | 0.79 | 0.69 | 0.50 | 0.47 | 0.66 | 0.48 | 0.47 |
|  |  |  |  |  |  |  |  |  |  |  |
|  | Validation | 0.69 | 0.62 | 0.73 | 0.76 | 0.94 | 0.54 | 0.72 | 0.76 | 0.53 |



Figure III. 15 - Histograms of WCM parameters when estimated all at once over 20102016 period (in blue) and over the 2010-2013 calibration period (in red). Approach 1 as described in Shamambo et al. (2019) is applied over southwestern France with WCM Option 1 ( $V_{1}=1$ ).


Figure III. 16 - As Figure III.15, except for calibration Approach 2.


Figure III. 17 - As Figure III.15, except for calibration Approach 3.


Figure III. 18 - As Figure III.15, except for calibration Approach 4.

## 3 Synthesis of Chapter III and conclusions

This chapter investigated the capacity of using the water cloud model (WCM) to simulate, together with the ISBA LSM, ASCAT $\sigma^{\circ}$ observations over different seasons and land cover types. Using four approaches of calibrating the WCM parameters and two versions of the WCM (sections 2.3 and 2.4), a quantitative analysis of differences between observed and simulated ASCAT $\sigma^{\circ}$ values was performed. Results showed that calibrating all four parameters of the WCM at once and using the WCM configuration corresponding to $V_{1}=1$ produced the best fit to the observations. Histogram analysis demonstrated that robust estimates of the four parameters of the WCM were obtained using the SCE-UA optimization method. Maps of the WCM parameters were compared with known geographical features and interesting patterns were noticed such as large values of the A parameter over large urban areas and small values of this parameter over the grassland cover type. Two case studies were performed over (1) the Euro-Mediterranean are, (2) southwestern France. In both cases, the overall performance of the WCM was good. However, small and negative values were noticed over some regions like low-altitude calcareous karstic areas, particularly during the dry season in Western Europe. A detailed study over the Landes forest showed that the WCM is able to describe the impact of the Klaus storm of January 2009 on the Landes forest provided that the LAI forcing is accurate enough and that the B parameter is recalibrated for the regeneration period. The B parameter has a seasonal cycle over wheat croplands and this signal could be used to better describe the seasonal variations of specific leaf area (SLA). The modelling of the ASCAT $\sigma^{\circ}$ observations using the WCM together with the ISBA LSM seems feasible in most environmental conditions. This result shows that the WCM could be considered as an observation operator to assimilate the ASCAT $\sigma^{\circ}$ observations in LDAS-Monde.

## CHAPTER IV - Assimilation of ASCAT $\sigma^{\circ}$ into the ISBA land surface model

The objective of this chapter is to assess the capacity of LDAS-Monde data assimilation tool to assimilate ASCAT radar backscatter observations and then evaluate the impact of assimilating these observations on leaf area index and soil moisture LSVs. Twelve locations in southwestern France were chosen to perform the assessment. They correspond to SMOSMANIA (Soil Moisture Observing System-Meteorological Automatic Network Integrated Application) stations that are located in southwestern France. Soil and climate characteristics are well documented for these locations, as well as the performance of the ISBA LSM. For example, Albergel et al. (2010) have shown that the simulated ISBA surface soil moisture is consistent with in situ soil moisture observations for most of these stations. These 12 stations are part of the 21 SMOSMANIA stations that have been established in southeastern and southwestern France in order to acquire automated soil moisture and soil temperature measurements (Calvet et al. 2007; Albergel et al. 2008, 2010, Parrens et al. 2012).

## 1 Introduction

Land surface variables such as leaf area index and soil moisture are key for monitoring the energy and water cycles. Simulation of these land surface variables by LSMs need to be consistent with the land surface conditions they are representing. Development of global satellite datasets has made it possible to observe geophysical variables on a large scale with improved temporal and spatial resolutions. In order to improve the simulation of land surface variables, LSMs can integrate satellite observations via data assimilation techniques. Several studies (Draper et al. 2012; Matgen et al. 2012; De Rosnay et al. 2013; Wanders et al. 2014; Ridler et al. 2014; Albergel et al. 2017, 2018a,b, 2020; Bonan et al. 2020; Kumar et al. 2018, 2020; Dharssi et al. 2011; Barbu et al. 2011; De Lannoy and Reichle 2016; Barbu et al. 2014; Boussetta et al. 2015; Fairbain et al. 2017; Leroux et al. 2018; Tall et al. 2019, Bonan et al. 2020, Mucia et al. 2020) have been successfully conducted to show how data assimilation can impact different geophysical variables and help improving their representation, monitoring and understanding. Despite proven advances in land data assimilating systems (LDASs), most of the LSMs have been customized to assimilate geophysical retrievals and not direct satellite observations. Assimilating the retrievals can increase the uncertainty errors in LSMs because of possible inconsistencies of these retrievals with the models. Moreover, cross-correlations can be found in cases where the geophysical retrievals and the model simulations rely on the same auxiliary data (De Lannoy and Reichle 2016; Lievens et al. 2017a). This might led to lowering the performance of the LDAS. There is now a tendency towards directly exploiting data closer to satellite sensor observations (e.g. level 1 radar $\sigma^{\circ}$ products) in data assimilation schemes in order to avoid the aforementioned factors that can degrade the performance of data assimilation approaches.

Level 1 observations such as radar $\sigma^{\circ}$ are usually not simulated by LSMs. In order to directly assimilate level 1 satellite observation products, the challenge of first creating an observation operator that thoroughly links the numerical model variables to this kind of satellite observations must be resolved. After the observation operator is established, carefully implementing the data assimilation system must be executed in such a way that numerous data assimilation problems are overcome so that the potential improvements from data assimilation can be achieved. Several studies (Crow et al. 2003; Reichle et al. 2001; Han et al. 2014; De Lannoy and Reichle 2016; Lievens et al. 2017b; Lin et al. 2017; León 2020) discussed the feasibility of directly assimilating such satellite observations in numerical models. It was shown that ASCAT radar $\sigma^{\circ}$ observations contain information on both soil moisture and vegetation dynamics (Schroeder et al. 2016, Vreugdenhil et al. 2016, Vreugdenhil et al. 2017, Steele-Dunne et al. 2019). Therefore, assimilating this dataset can probably enhance the representation of these key LSVs. Few studies have however exploited the possibility of assimilating ASCAT $\sigma^{\circ}$ in LSMs. For instance Lievens et al. (2017a) built an observation operator to link ASCAT $\sigma^{\circ}$ to soil moisture and VOD (microwave Vegetation Optical Depth) in the GLEAM LSM. The soil moisture product they used was the soil moisture of the top soil layer of the GLEAM model. The VOD product they used was not directly simulated by GLEAM but since GLEAM already utilized VOD as one of its forcing dataset to represent the water stress of the vegetation, this geophysical variable was also used as a vegetation descriptor to help couple the observation operator to the model. The ISBA LSM on the other hand is able to simulate both soil moisture and LAI.

The LAI simulated by ISBA can be directly used as vegetation descriptor when linking the ISBA model variables to the ASCAT radar backscatter coefficient.

In this Chapter, results are given for locations corresponding to the 12 westernmost SMOSMANIA stations (Figure IV.1). They are all in southwestern France. Additional illustrations are presented for a subset of 6 stations (CDM, CRD, SBR, PRG, LHS and MTM) presenting contrasting geographical locations and soil characteristics in order to understand the impact of data assimilation under diverse environmental conditions. Station CRD and SBR are characterized by sandy soil texture, with station SBR being located in the Landes forest. Stations CDM, LHS and PRG are characterized by clay soil textures with each station being located at least 45 km apart. Lastly, station MTM is located on a karstic area.


Figure IV. 1 - Location of the 21 SMOSMANIA stations in southern France and the locations over which data assimilation was tested corresponding to the 12 wersternmost SMOSMANIA stations (within the blue box). Adapted from Zhang et al. 2019. Station full names and soil characteristics can be found in the Supplement of Calvet et al. 2016.


Figure IV. 2 - ASCAT $\sigma^{\circ}$ (sigma0_OBS) observations response to surface soil moisture (SSM) from ISBA ( $\mathbf{w g}_{2}$ ) and CGLS LAI for (a) CDM (b) PRG (c) LHS and (D) MTM stations. LAI $\mathbf{0 \%} \mathbf{- 2 0 \%}, \mathbf{2 1 \% - 7 9 \%}, \mathbf{8 0 \% - 1 0 0 \%}$ percentile classes are indicated (red dots, blue triangles, and green stars, respectively).

## 2 Implementation of the Land Data Assimilation System

### 2.1 Datasets and data processing

The ISBA model is linked to the WCM (Water Cloud Model) through vegetation and soil water content variables then providing a scheme that offers the possibility to simulate radar backscatter coefficients. The radar $\sigma^{\circ}$ observations are obtained from ASCAT sensors and are also referred to as ASCAT $\sigma^{\circ}$ in this work. The production of $\sigma^{\circ}$ simulations is executed as described in Figure III. 2 (Chapter III). LAI observations from the Copernicus Global Land service (CGLS) were used as a vegetation proxy in the WCM together with surface soil moisture (SSM) from the ISBA soil layer $2\left(\mathrm{wg}_{2}\right)$ to calibrate the WCM model (Shamambo et al. 2019). The WCM parameters (A, B, C and D) were fitted all at once using the Approach 1 described in Section 2.4 of Chapter III. Figure IV. 2 shows how LAI observations and ISBA simulated soil moisture $\left(\mathrm{wg}_{2}\right)$ are related to ASCAT $\sigma^{\circ}$ observations over the CDM, PRG, LHS and MTM stations. For the four stations, we see that there is no clear linear relationship between the $\mathrm{wg}_{2}$ and ASCAT $\sigma^{\circ}$ under the different LAI classes considered. The histograms for each graph show that the $\mathrm{wg}_{2}$ simulations tend to present a bimodal statistical distribution with two classes representative of wet and dry conditions, intermediate values being less frequent. On the other hand, the ASCAT $\sigma^{\circ}$ do not present such a clear bimodal statistical distribution, especially for the MTM station. The $\sigma^{\circ}$ distribution of the MTM station is more Gaussian than that of CDM, PRG and LHS. Apart from ISBA soil moisture simulations, soil moisture observations from the CGLS called SWI-001 are also used in this work for further evaluations. In order to address the bias between simulated ISBA soil moisture product and the observed SWI-001 soil moisture product, the later was rescaled to the ISBA model climatology using cumulative distribution function (CDF) as detailed in Albergel et al. (2017). Under this chapter, the evaluation metrics consisting of Pearson correlation coefficient $(R)$, mean bias and root mean squared differences (RMSD) are used to determine the impact of assimilating ASCAT $\sigma^{\circ}$ on the different state variables involved.

### 2.2 Implementation of the water cloud model (WCM) in the Simplified Extended Kalman Filter (SEKF)

This subsection is mainly concerned with how the WCM is implemented in the SEKF approach that is routinely used in LDAS-Monde. The SEKF equations are described in Chapter II, Eq. II.1-II.4. The analysis update is described in Eq. II. 2 where the Kalman gain K is estimated using a Jacobian matrix (J) that involves H and M (see Eq. IV.1) with H being the observation operator and M the model which gives the forecast initial variables.

$$
\begin{equation*}
J=\frac{\partial H\left(M_{0}\left(x_{t(0)}^{a}\right)\right)}{\partial x_{t(0)}^{a}} \tag{IV.1}
\end{equation*}
$$

For this study, the WCM was used as the observation operator (H) and the version of ISBA able to simulate LAI is the model employed. The Jacobian of the observation operator is calculated using the finite differences approach. This follows the same approach
developed for LDAS-Monde to assimilate LAI and surface soil moisture and involves running the model several times from perturbed initial states. Each element of the Jacobian matrix can be noted using a simplified expression as in Eq. IV.2:

$$
\begin{equation*}
[J]_{n m}=\frac{\partial[H]_{n}}{\partial[x]_{m}} \tag{IV.2}
\end{equation*}
$$

with the term $x$ representing the control vector of dimension $m$, representing the number of control variables, and H is the vector of the observations with dimension $n$, representing the number of observations.

In this experiment, the control vector $x$ consists of 8 simulated variables $(m=8)$ :

- LAI,
- $\mathrm{wg}_{2}$ (soil moisture for layer 2,1-4 cm depth)
- $\mathrm{wg}_{3}$ (soil moisture for layer 3, 4-10 cm depth),
- $\mathrm{wg}_{4}$ (10-20 cm depth),
- $\mathrm{wg}_{5}(20-40 \mathrm{~cm}$ depth),
- $\mathrm{wg}_{6}(40-60 \mathrm{~cm}$ depth $)$,
- $\mathrm{wg}_{7}$ (60-80 cm depth) and
- $\mathrm{wg}_{8}$ (80-100 cm depth).

The ASCAT signal is sensitive to LAI and to SSM only. However, soil moisture of deep soil layers in the ISBA LSM can impact the simulated LAI through the functional relationship between the soil water deficit and photosynthesis and between photosynthesis and plant growth and senescence. It can also impact SSM through water diffusion processes.

As for the observation vector of dimension $n$, radar backscatter observations ( $\sigma^{\circ}$ ) are used and $n=1$. It leads to the following Jacobian matrix

$$
\begin{equation*}
J=\left(\frac{\partial \sigma_{t 1}^{f}}{\partial L A I_{t 0}} \frac{\partial \sigma_{t 1}^{f}}{\partial w g 2_{t 0}} \ldots \frac{\partial \sigma_{t 1}^{f}}{\partial w g 8_{t 0}}\right) \tag{IV.3}
\end{equation*}
$$

where $\sigma^{\mathrm{f}}$ is the output of the WCM at time $\mathrm{t}_{1}$. Equation IV. 4 details how the first element of J related to the LAI control vector is calculated in terms of simulated $\sigma^{\circ}$ sensitivity to LAI using the finite differences method:

$$
\begin{equation*}
[J]_{11}=\frac{\partial \sigma_{t 1}^{f}}{\partial L A I_{t 0}}=\frac{W C_{t 1}^{\text {model }}\left(M_{0}\left(x_{t(0)}^{a}+\partial L A I\right)\right)-W C_{t 1}^{\text {model }}\left(M_{0}\left(x_{t(0)}^{a}\right)\right)}{\partial L A I} \tag{IV.4}
\end{equation*}
$$

To calculate $[J]_{11}$, a model run initialized with a perturbed LAI at $t_{0}$ is needed in addition to the model run used for the forecast.

As for soil moisture control vectors, examples of how each variable can be calculated are expressed by Eq. IV. 5 (for $\mathrm{wg}_{2}$ ) and Eq. IV. 6 (for $\mathrm{wg}_{8}$ ). For the other soil moisture layers ( $\mathrm{wg}_{3}$ to $\mathrm{wg}_{7}$ ), their calculation can be obtained by just substituting either $\mathrm{wg}_{2}$ or $\mathrm{wg}_{8}$ from equations IV. 5 and IV. 6 respectively with the layer to be calculated.

$$
\begin{align*}
& {[J]_{12}=\frac{\partial \sigma_{t 1}^{f}}{\partial w g 2_{t 0}}=\frac{W C_{t 1}^{\text {model }}\left(M_{0}\left(x_{t(0)}^{a}+\partial w g 2\right)\right)-W C_{t 1}^{\text {model }}\left(M_{0}\left(x_{t(0)}^{a}\right)\right)}{\partial w g 2}}  \tag{IV.5}\\
& {[J]_{18}=\frac{\partial \sigma_{t 1}^{f}}{\partial w g 8_{t 0}}=\frac{W C_{t 1}^{\text {model }}\left(M_{0}\left(x_{t(0)}^{a}+\partial w g 8\right)\right)-W C_{t 1}^{\text {model }}\left(M_{0}\left(x_{t(0)}^{a}\right)\right)}{\partial w g 8}}
\end{align*}
$$

(IV.6).

To calculate $[\mathrm{J}]_{12}$, a model run initialized with a perturbed $\mathrm{wg}_{2}$ at $\mathrm{t}_{0}$ is needed in addition to the model run used for the forecast. The calculation of $[J]_{18}$ involves also a model run initialized with a perturbed $\mathrm{wg}_{8}$ at $\mathrm{t}_{0}$. In total, 8 perturbed runs in addition to the model run used for the forecast are needed to compute the Jacobian matrix since there are 8 control variables.

### 2.3 Configuration of LDAS-Monde

In this study, the flow chart on Figure IV. 3 shows the different procedures involved in assimilating ASCAT $\sigma^{\circ}$ observations. In this flowchart, the ISBA model is forced by the ERA5 atmospheric forcing and static soil and vegetation parameters from ECOCLIMAP. ISBA simulates LAI and SSM that are fed into the WCM as control variables for data assimilation purposes. Before the assimilation process, the WCM is first used to simulate $\sigma^{\circ}$ measurements. The WCM parameters are those previously fitted based on ASCAT $\sigma^{\circ}$ observations using the SCE-UA optimization method as described in Shamambo et al. (2019). This means that the WCM is based on inputs of satellite LAI observations from CGLS and of surface soil moisture from ISBA simulations, aggregated to grid cells of $0.25^{\circ}$ $\times 0.25^{\circ}$. The processes related to the WCM parameter calibration are displayed with red arrows and boxes in Figure IV.3. The model simulations and the used datasets are illustrated by the blue arrows and boxes. The updating of ISBA LSM through the assimilation of ASCAT $\sigma^{\circ}$ observations by implementing the WCM model in the SEKF data assimilation scheme produces new state updates that are also called "analysis". Parts representing the SEKF data assimilation scheme are represented by dashed arrows and boxes in green. The LDAS-Monde configuration used is as illustrated in Figure II. 5 (Chapter II) where $x$ is the eight dimensional control vector consisting of LAI and the different soil layers (layer 2 to layer 8) representing a soil root-zone layer ranging from 1 cm to 100 cm depth. The ASCAT $\sigma^{\circ}$ observations used are contained in the vector represented by term $y_{0}$ in Eq. II.2. The "model equivalent" of the ASCAT $\sigma^{\circ}$ observations are the simulated $\sigma^{\circ}$ values that are obtained from the WCM, with the later acting as an observation operator (more details in Chapter II, section 4). LDAS-Monde employs a 24 hour assimilation window. Each sequence of the assimilation window consists of two steps: forecast and analysis. The forecast stage involves propagating the initial state variables from a time $t$ to $t+24$ using the ISBA model. Each ISBA grid has patches that do not interact with each other. The propagated initial state variables offer the perturbed model runs that are used to calculate the Jacobians as elaborated by Eqs. IV. 1 to IV.6. The ASCAT $\sigma^{\circ}$ observations are assimilated into ISBA on a daily basis with only the anomalies of the observations and forecast being used in the state Eq. II.2.

The procedure consists of running the first year (2007) 20 times during in order to ensure a physically realistic state of equilibrium in ISBA for each SMOSMANIA location
considered. Thereafter, a sequential data assimilation technique called SEKF represented by elements in the green dotted box (Figure IV.2) is performed together with its openloop equivalent (model run only, with no data assimilation) as detailed in Tall et al. (2019). This openloop experiment is useful as it helps studying the model sensitivity to the assimilation of $\sigma^{0}$ observations. The Jacobians, J (Eq. IV.2), are dependent on the model physics and their examination provides very useful insight into explaining the data assimilation system performances (Barbu et al. 2011; Fairbairn et al. 2017, Albergel et al. 2017).

The background error for soil moisture is set to $0.04 \mathrm{~m}^{3} \mathrm{~m}^{-3}$ for the second layer soil moisture and $0.02 \mathrm{~m}^{3} \mathrm{~m}^{-3}$ for soil moisture in deeper layers. Regarding the fixed background errors of the LAI variable, a standard deviation of $20 \%$ for LAI values larger than $2 \mathrm{~m}^{2} \mathrm{~m}^{-2}$, and $0.04 \mathrm{~m}^{2} \mathrm{~m}^{-2}$ for values LAI smaller than $2 \mathrm{~m}^{2} \mathrm{~m}^{-2}$ were prescribed. More details concerning background error setting for LAI and soil moisture for LDAS-Monde can be found in Bonan et al. (2020) and Albergel et al. (2019).

The soil moisture perturbations used in the Jacobian matrix are presumed to be commensurate to the main dynamic range of soil moisture (the difference between the volumetric field capacity, $w_{\mathrm{fc}}$, and the wilting point, $w_{\text {wilt }}$ ) according to Draper et al. (2011) and Mahfouf et al. (2009). A value of $1 \times 10^{-4} \times\left(w_{\mathrm{fc}}-w_{\text {wilt }}\right)$ is attributed to Jacobian perturbations of the soil moisture variables. As for the Jacobian perturbation of the LAI variable, a perturbation of $0.001 \mathrm{~m}^{2} \mathrm{~m}^{-2}$ following the research studies of Rüdiger et al. (2010) was used. These perturbation settings are equivalent to what was used in other studies (Albergel et al. 2017; Bonan et al. 2020).

Coming to the part concerning ASCAT $\sigma^{\circ}$ observations, a fixed observation error of 0.33 dB is used, following Lievens et al. (2017a). It is important to note that no attempt was made in the PhD work to refine this value. More research is needed to estimate the optimal observation error to use for assimilating ASCAT $\sigma^{\circ}$ observations.


Figure IV. 3 - Flowchart of data and methods used in this study for model calibration of the WCM (elements associated with arrows and boxes in red), model simulation (elements associated with arrows and boxes in blue) and SEKF assimilation scheme (elements associated with dashed arrows and dashed boxes in green).

Under this section, the impact of assimilating ASCAT $\sigma^{\circ}$ observations in ISBA is evaluated and the subsections that follow outline the obtained results.

### 3.1 Model sensitivity to the observations

In order to comprehend the performance of the data assimilation system, it is important to analyze the model sensitivity to the observations. The Jacobian as expressed by Eq. II. 4 in Chapter II is a fundamental part of the data assimilation process for the simplified extended Kalman filter (SEKF) technique used in this work. Each element of the Jacobian is controlled by the model physics and corresponds to the model sensitivity to the observations as decribed in other studies (Rüdiger et al. 2010, Barbu et al. 2011, Tall et al. 2019, Albergel et al. 2017). The ISBA model provides initial conditions for eight variables (LAI, $\mathrm{wg}_{2}$ ( 1 to 4 cm ), $\mathrm{wg}_{3}\left(4\right.$ to 10 cm ), $\mathrm{wg}_{4}\left(10\right.$ to 20 cm ), $\mathrm{wg}_{5}\left(20\right.$ to 40 cm ), $\mathrm{wg}_{6}$ ( 40 to $60 \mathrm{~cm}), \mathrm{wg}_{7}(60$ to 80 cm$)$ and $\mathrm{wg}_{8}(80$ to 100 cm$)$ ) that are used as control variables simulated during the assimilation window. For the sake of clarity, only the sensitivity of $\sigma^{\circ}$ to changes in LAI (Jacobian LAI) and in soil moisture (Jacobian $\mathrm{wg}_{2}$, Jacobian $\mathrm{wg}_{4}$ and Jacobian $\mathrm{wg}_{6}$ ) is presented.

Figures IV. 4 to IV. 9 indicate the seasonal cycles of the Jacobians averaged from January 2007 to December 2016 over SBR, CRD, PRG, CDM, LHS and MTM stations, respectively.

Looking at the sensitivity of $\sigma^{\circ}$ to changes in soil moisture variables, it can be noticed that Jacobian $\mathrm{wg}_{2}$ tends to peak in September, with larger values from July to September or October than what is observed for deeper soil layers. Jacobian $\mathrm{wg}_{4}$ and Jacobian $\mathrm{wg}_{6}$ tend to peak from December to March and Jacobian $\mathrm{wg}_{4}$ is larger than other soil moisture Jacobians from November to May. This means that $\mathrm{wg}_{4}$ is more likely to be impacted by the assimilation at wintertime and at spring than other soil layers. The same seasonal behavior is observed for $\mathrm{wg}_{6}$ with a much reduced sensitivity. On the other hand, the top soil layer $\left(\mathrm{wg}_{2}\right)$ is more likely to be impacted by the assimilation during the vegetation senescence. This implies that the skill of the assimilation of ASCAT $\sigma^{\circ}$ to predict better soil moisture estimates can vary from one soil layer to another across seasons. However, soil moisture is also impacted by changes in LAI values caused by the assimilation because the LAI control variable is impacted by the assimilation of $\sigma^{\circ}$. Analysis increments in Figures IV. 4 to IV. 9 indicate for example that marked $w g_{4}$ negative increments observed from February to March correspond to positive increments of LAI that generally result in larger LAI values in March and April. The latter can induce an increase in plant transpiration that triggers smaller soil moisture values in April. Larger LAI values in the analysis are also observed in September and October and they correspond to smaller soil moisture values. September is the month with the highest values of Jacobian LAI at all locations. It must be noticed that the impact of the assimilation on $\mathrm{wg}_{6}$ during the autumn is delayed by one month with respect to $\mathrm{wg}_{2}$ and to $\mathrm{wg}_{4}$ for CRD, PRG, CDM, LHS and MTM. Apart from SBR and MTM, the assimilation of $\sigma^{\circ}$ tends to slightly increase LAI values in March and September and to decrease them in July. The SBR and MTM stations are quite different from the other stations located in agricultural areas: SBR is located in the Landes forest (affected by the Klaus storm in January 2019 as discussed in Chaper III) and MTM is close to a karstic area (not simulated well by the WCM as shown in Chapter II and in Chapter III).


Figure IV. 4 - Monthly average seasonal evolution from 2007-2016 over the SBR station of: (a) Jacobians for LAI (red line), $\mathrm{wg}_{2}$ (green dashed line), $\mathrm{wg}_{4}$ (blue dashed line) and $\mathbf{w g}_{6}$ (yellow dashed line); (b) daily analysis increments for LAI (red line), $\mathbf{w g}_{2}$ (green dashed line), $\mathrm{wg}_{4}$ (blue dashed line) and $\mathrm{wg}_{6}$ (yellow dashed line); (c) analysis minus openloop for LAI variable (red line) (d) analysis minus openloop for $\mathbf{w g}_{2}$ (green dashed line), $\mathbf{w g}_{4}$ (blue dashed line) and $\mathbf{w g}_{6}$ (yellow dashed line).


Figure IV. 5 - As in Figure IV.4, except for the CRD station.


Figure IV. 6 - As in Figure IV.4, except for the PRG station.


Figure IV. 7 - As in Figure IV.4, except for the CDM station.


Figure IV. 8 - As in Figure IV.4, except for the LHS station.


Figure IV. 9 - As in Figure IV.4, except for the MTM station.

### 3.2 Impact of the WCM sensitivity to the assimilation on LAI

One of the advantages of assimilating ASCAT $\sigma^{\circ}$ values instead of ASCAT-derived SSM estimates is that the former can give direct information on vegetation density in certain conditions. Figures IV. 4 to IV. 9 show that the LAI Jacobian has a seasonal cycle with negative values at wintertime and with largest positive values in September. This can be explained by the fact that wet conditions are generally observed at wintertime and the driest conditions are observed at the end of the summer season. The WCM tends to predict larger $\sigma^{\circ}$ values in response to an increase of LAI in dry conditions and vice versa in wet conditions (see Figure 9 in Shamambo et al. 2019). The threshold soil moisture condition separating these two responses of $\sigma^{\circ}$ to changes in LAI is a critical SSM value $\left(\mathrm{SSM}_{\mathrm{C}}\right)$ depending on $A, C$, and $D$ parameters of the WCM (see Eq. (8) in Shamambo et al. 2019). Table IV. 1 lists the WCM parameter values and scores together with SSM $_{C}$ and in situ observations of the porosity. Since SSM $_{C}$ values are much larger than 0 while being smaller than the porosity (i.e. than the maximum observable SSM value), the two responses of $\sigma^{\circ}$ to changes in LAI can be observed. When the simulated SSM is equal to $\mathrm{SSM}_{\mathrm{C}}$ (i.e. under intermediate soil moisture conditions) the simulated $\sigma^{\circ}$ is not directly influenced by LAI. Table IV. 1 also shows that the lowest $R$ score $(R=0.31)$ of the WCM is obtained for the MTM station. This confirms the detrimental impact of the karst perturbing factor on the performance of the WCM.

Table IV. 1 - Water cloud model (WCM) parameters ( $A, B, C$, and $D$ ) values for the 12 SMOSMANIA stations in southwestern France and their statistical score (RMSD, R, and mean bias) between simulated and observed $\sigma^{\circ}$, together with the critical surface soil moisture ( $\mathbf{S S M}_{\mathrm{C}}$ ) calculated from $A, C$, and $D$ parameters and in situ observations of the porosity of the top soil layer (Calvet et al. 2016).

| Stations | WCM Parameter Values |  |  |  | $\begin{gathered} \operatorname{SSM}_{\mathrm{C}} \\ \left(\mathrm{~m}^{3} \mathrm{~m}^{-3}\right) \end{gathered}$ | Porosity$\left(m^{3} m^{-3}\right)$ | WCM statistical scores |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | A | $B$ | $C \quad(\mathrm{~dB})$ | $D \quad(\mathrm{~dB})$ |  |  | $R$ | RMSD <br> (dB) | Bias (dB) |
| SBR | 0.11 | 0.24 | -16.0 | 28.7 | 0.18 | 0.35 | 0.78 | 0.46 | -0.05 |
| URG | 0.15 | 0.32 | -17.2 | 26.9 | 0.29 | 0.47 | 0.76 | 0.38 | 0.01 |
| CRD | 0.14 | 0.29 | -17.1 | 27.8 | 0.27 | 0.44 | 0.77 | 0.34 | -0.02 |
| PRG | 0.14 | 0.40 | -18.2 | 27.4 | 0.31 | 0.43 | 0.71 | 0.44 | 0.06 |
| CDM | 0.13 | 0.51 | -17.4 | 28.1 | 0.26 | 0.41 | 0.71 | 0.55 | 0.01 |
| LHS | 0.13 | 0.51 | -17.1 | 27.5 | 0.26 | 0.42 | 0.67 | 0.69 | -0.07 |
| SVN | 0.15 | 0.41 | -16.4 | 28.6 | 0.24 | 0.45 | 0.71 | 0.57 | 0.04 |
| MNT | 0.14 | 0.50 | -18.1 | 27.9 | 0.30 | 0.45 | 0.65 | 0.47 | 0.03 |
| SFL | 0.14 | 0.59 | -17.8 | 27.4 | 0.30 | 0.41 | 0.62 | 0.70 | -0.02 |
| MTM | 0.16 | 0.43 | -18.7 | 28.1 | 0.34 | 0.41 | 0.31 | 0.34 | -0.13 |
| LZC | 0.15 | 0.75 | -18.0 | 28.5 | 0.30 | 0.43 | 0.43 | 0.33 | 0.05 |
| NBN | 0.14 | 0.84 | -18.9 | 27.9 | 0.33 | 0.40 | 0.34 | 0.38 | 0.00 |

LAI time series for SBR station


LAI time series for LHS station


LAI time series for MTM station


Figure IV. 10 - Leaf area index time series from the openloop (blue dashed line), the observations (green dashed line), and the analysis (red line) from 2007 to 2016 for (from top to bottom) the SBR, CRD, LHS, MTM stations.

The impact of the assimilation of ASCAT $\sigma^{\circ}$ observations on the simulated LAI time series is presented in Figure IV. 10 for four locations: SBR, CRD, LHS, and MTM. The CGLS LAI observations are also shown. For CRD, the simulated LAI is relatively close to the observations and the assimilation has little impact on LAI. On the other hand, the assimilation tends to decrease the simulated LAI at the end of the year for the other stations. This is consistent with the negative increments observed in November in Figures IV. 4 to IV.9. The LHS station presents the largest impact of the assimilation on LAI. Interestingly, this impact is much marked in 2011 at LHS throughout the plant growing season. The 2011 year was characterized by a severe spring drought that triggers drier soil conditions and the assimilation of $\sigma^{\circ}$ observations is efficient in reducing the error of the simulated LAI.

In general, the analysis tends to slightly reduce the error of the simulated LAI, except for the MTM location. Again, this can be explained by the detrimental impact of the karst perturbing factor on the performance of the WCM.

### 3.3 Overall performance of the assimilation of ASCAT $\sigma^{\circ}$ observations

Table IV. 2 presents scores of the analyzed SSM and LAI resulting from the assimilation of ASCAT $\sigma^{0}$ with an uncertainty of 0.33 dB for the 12 SMOSMANIA stations presented in Figure IV.1. In Table IV.1, the SSM and LAI benchmark datasets consist of time series derived from global products disseminated by CGLS: the ASCAT SWI product corresponding to the top soil layer and the true LAI (derived from SPOT-Vegetation and PROBA-V data), respectively. For the comparison, ASCAT SWI is converted in SSM values in $\mathrm{m}^{3} \mathrm{~m}^{-3}$ with the same seasonal linear rescaling employed to assimilate ASCAT SWI in LDAS-Monde.

Both open-loop and analysis simulations present a good correlation with the reference SSM and LAI datasets, ranging from $R=0.6$ for SSM over the MTM station to $R$ $=0.9$ for LAI over the CRD station.

The RMSD scores of SSM and LAI range from $0.023 \mathrm{~m}^{3} \mathrm{~m}^{-3}$ over SBR to 0.050 $\mathrm{m}^{3} \mathrm{~m}^{-3}$ over MTM and from $0.4 \mathrm{~m}^{2} \mathrm{~m}^{-2}$ to $1.4 \mathrm{~m}^{2} \mathrm{~m}^{-2}$ over SFL, respectively.

The SSM simulations are nearly unbiased because rescaled ASCAT SWI values are used as a benchmark. On the other hand, the LAI bias can be quite large. It varies from 0.2 $\mathrm{m}^{2} \mathrm{~m}^{-2}$ over CRD to $1.0 \mathrm{~m}^{2} \mathrm{~m}^{-2}$ over SFL.

The assimilation of ASCAT $\sigma^{0}$ has a slightly positive to neutral impact on the SSM scores, and no negative impact is observed at any location. On the other hand, the impact of the assimilation on LAI can be substantial. A positive impact on LAI is observed for SBR, LHS, SFL, and to a lesser extent for SVN, MNT, LZC and NBN. A slightly negative impact on LAI is observed for MTM in terms of mean bias and RMSD. For SBR, LHS, and SFL the $R$ score increases from 0.7 to 0.8 and RMSD is decreased by about $0.1 \mathrm{~m}^{2} \mathrm{~m}^{-2}$.

Table IV. 2 - Statistics (RMSD: root mean square difference, $R$ : correlation, and mean bias) between LDAS-Monde estimates (open loop, analysis based on the assimilation of ASCAT $\sigma^{0}$ with an uncertainty of 0.33 dB ) and observations for CGLS true leaf area index (LAI $\left[\mathrm{m}^{2} \mathrm{~m}^{-2}\right]$ ), and ASCAT Soil Water Index (SSM $\left[\mathrm{m}^{3} \mathrm{~m}^{-3}\right]$ ) over each SMOSMANIA station examined for the period 2007-2016. Note that for the comparison, ASCAT SWI is converted to Surface Soil Moisture (SSM $\left[\mathrm{m}^{3} \mathrm{~m}^{-3}\right]$ ) with the same seasonal linear rescaling employed to assimilate ASCAT SWI in LDASMonde. Improved (degraded) scores of the analysis with respect to the open-loop are in bold and blue (red).

| Station | Variable | Experiment | $\boldsymbol{R}$ | RMSD | Mean <br> bias | Observations' number |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| SBR | SSM | open-loop | 0.85 | 0.025 | 0.001 | 1360 |
|  |  | analysis | 0.86 | 0.023 | 0.000 |  |
|  | LAI | open-loop | 0.72 | 0.76 | 0.39 | 360 |
|  |  | analysis | 0.79 | 0.67 | 0.23 |  |
| URG | SSM | open-loop | 0.89 | 0.029 | 0.003 | 1492 |
|  |  | analysis | 0.89 | 0.028 | 0.002 |  |
|  | LAI | open-loop | 0.78 | 0.88 | 0.53 | 360 |
|  |  | analysis | 0.78 | 0.89 | 0.55 |  |
| CRD | SSM | Open-loop | 0.88 | 0.028 | 0.002 | 1483 |
|  |  | analysis | 0.89 | 0.028 | 0.002 |  |
|  | LAI | open-loop | 0.90 | 0.43 | 0.17 | 360 |
|  |  | analysis | 0.90 | 0.43 | 0.17 |  |
| PRG | SSM | open-loop | 0.87 | 0.034 | 0.003 | 1444 |
|  |  | analysis | 0.87 | 0.033 | 0.001 |  |
|  | LAI | open-loop | 0.64 | 1.18 | 0.76 | 360 |
|  |  | analysis | 0.64 | 1.12 | 0.77 |  |

Table IV. 2 - continued.

| Station | Variable | Experiment | $\boldsymbol{R}$ | $\mathbf{R M S D}$ | Mean <br> bias | Observa- <br> tions' num- <br> ber |
| :---: | :--- | :--- | :---: | :---: | :---: | :---: |
| CDM | SSM | LAI | Open-loop | 0.84 | 0.036 | 0.003 |

Table IV. 2 - end.

| Station | Variable | Experiment | $\boldsymbol{R}$ | RMSD | Mean bias | Observations' number |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| SFL | SSM | open-loop | 0.82 | 0.040 | 0.004 | 1586 |
|  |  | analysis | 0.83 | 0.039 | -0.001 |  |
|  | LAI | open-loop | 0.67 | 1.40 | 0.99 | 360 |
|  |  | analysis | 0.75 | 1.32 | 0.98 |  |
| MTM | SSM | open-loop | 0.60 | 0.050 | 0.002 | 1632 |
|  |  | analysis | 0.60 | 0.050 | 0.002 |  |
|  | LAI | open-loop | 0.82 | 0.88 | -0.66 | 360 |
|  |  | analysis | 0.83 | 0.93 | -0.73 |  |
| LZC | SSM | open-loop | 0.78 | 0.037 | 0.002 | 1665 |
|  |  | analysis | 0.78 | 0.037 | 0.002 |  |
|  | LAI | open-loop | 0.81 | 0.66 | 0.38 | 360 |
|  |  | analysis | 0.85 | 0.59 | 0.34 |  |
| NBN | SSM | open-loop | 0.79 | 0.039 | 0.002 | 1630 |
|  |  | analysis | 0.79 | 0.038 | 0.002 |  |
|  | LAI | open-loop | 0.81 | 0.51 | 0.25 | 360 |
|  |  | analysis | 0.83 | 0.44 | 0.20 |  |

(a)


- Analysis
(c)

- Analysis


## (e)

RMSD $\left[m^{2} \mathrm{~m}^{-2}\right]$ with LAI obs (MTM station)

(b)


- Open Loop
(d)

- Open Loop
(f)


Figure IV. 11 - Leaf area index (LAI) seasonal (a,c,e) RMSD and (b,d,f) $R$ scores of openloop (blue line) and the analysis (red line) from 2007 to 2016 with respect to CGLS LAI for (a,b) the CRD station, (c,d) the LHS station, (e,f) the MTM station.


Figure IV. 12 - Surface soil moisture (SSM) seasonal (a,c,e) RMSD and (b,d,f) $R$ scores of openloop (blue line) and the analysis (red line) from 2007 to 2016 with respect to ASCAT SWI for (a,b) the CRD station, (c,d) the LHS station, (e,f) the MTM station.

In order to assess the seasonal impact of the assimilation of ASCAT $\sigma^{0}$ on LAI and SSM, Figures IV. 11 and IV. 12 present monthly RMSD and $R$ scores of LAI and SSM, respectively. The scores are presented for the CRD, LHS and MTM locations. The CRD station (see Table IV.1) is simulated well by the open-loop and the simulation is not changed much by the assimilation of ASCAT $\sigma^{0}$. On the other hand, open-loop and analysis simulations fot LHS tend to differ. Finally the assimilation is rather detrimental to the ISBA simulation over MTM, which can be explained again by the correspondence of this location with a karstic area.

While the SSM scores are nearly systematically improved by the assimilation over LHS, positive impacts on LAI are mainly observed during the plant growing phase. In particular, both RMSD and $R$ scores are improved in June.

The impact of the assimilation on CRD SSM and LAI variables is weak but SSM is improved at wintertime from December to March and the LAI $R$ score is improved at spring from March to May and during the autumn from September to November.

Over MTM, a negative impact of the assimilation on LAI is observed, mainly at springtime from March to May.

The evaluation performed above is informative but it cannot be considered as an independent direct validation of the assimilation because the benchmark SSM is derived from the same ASCAT $\sigma^{0}$ that are assimilated and because the benchmark LAI is used in the calibration of the WCM observation operator. An attempt was made to use the in situ soil moisture observations to validate the simulations. Table IV. 3 shows the openloop and analysis $R$ scores for the 12 SMOSMANIA stations. Table IV. 4 shows the anomaly correlations calculated by rescaling each soil moisture estimate at day $i$ using the average soil moisture value and standard deviation over a 5 -week window $[-17 \mathrm{~d}, i+17 \mathrm{~d}]$. The methodology is similar to the one employed in previous studies such as Albergel et al. (2018). The difference between openloop and analysis $R$ scores is small and does not exceed 0.01 . When a difference exist, the number of positive and negative changes in absolute $R$ values is about the same (Table IV.3). On the other hand, it is interesting to note that nearly all changes in anomaly $R$ values are positive (Table IV.3).

Table IV. 3 - Correlations between LDAS-Monde estimates (openloop, analysis) and in situ measurements from the SMOSMANIA network over the period 2007-2016. Improved (degraded) scores of the analysis with respect to the open-loop are in bold and blue (red).

| Station | Experiment | 5 cm depth | 10 cm depth | 20 cm depth | 30 cm depth |
| :---: | :---: | :---: | :---: | :---: | :---: |
|  | openloop | 0.52 | 0.42 | 0.46 | 0.25 |
| SBR | analysis | 0.53 | 0.43 | 0.47 | 0.25 |
|  | openloop | 0.75 | 0.73 | 0.69 | 0.71 |
| URG | analysis | 0.75 | 0.73 | 0.70 | 0.71 |
|  | openloop | 0.70 | 0.68 | 0.70 | 0.67 |
| CRD | analysis | 0.70 | 0.69 | 0.70 | 0.67 |
|  | openloop | 0.70 | 0.68 | 0.68 | 0.67 |
| PRG | analysis | 0.71 | 0.69 | 0.68 | 0.68 |
|  | openloop | 0.69 | 0.68 | 0.66 | 0.68 |
| CDM | analysis | 0.69 | 0.67 | 0.66 | 0.67 |
|  | openloop | 0.71 | 0.64 | 0.59 | 0.62 |
| LHS | analysis | 0.71 | 0.63 | 0.58 | 0.62 |
|  | openloop | 0.67 | 0.69 | 0.67 | 0.70 |
| SVN | analysis | 0.67 | 0.68 | 0.66 | 0.69 |
|  | openloop | 0.71 | 0.67 | 0.69 | 0.63 |
| MNT | analysis | 0.71 | 0.67 | 0.68 | 0.63 |
|  | openloop | 0.70 | 0.67 | 0.71 | 0.70 |
| SFL | analysis | 0.70 | 0.67 | 0.70 | 0.68 |
|  | openloop | 0.58 | 0.61 | 0.60 | 0.57 |
| MTM | analysis | 0.59 | 0.61 | 0.60 | 0.58 |
|  | openloop | 0.67 | 0.65 | 0.69 | 0.66 |
| LZC | analysis | 0.67 | 0.65 | 0.69 | 0.66 |
|  | openloop | 0.75 | 0.76 | 0.74 | 0.73 |
| NBN | analysis | 0.75 | 0.75 | 0.74 | 0.72 |

Table IV. 4 - Anomaly correlations between LDAS-Monde estimates (openloop, analysis) and in situ measurements from the SMOSMANIA network over the period 2007 - 2016. Improved (degraded) scores of the analysis with respect to the open-loop are in bold and blue (red).

| Station | Experiment | 5 cm depth | 10 cm depth | 20 cm depth | 30 cm depth |
| :---: | :---: | :---: | :---: | :---: | :---: |
|  | open-loop | 0.64 | 0.65 | 0.64 | 0.61 |
| SBR | analysis | 0.65 | 0.65 | 0.64 | 0.62 |
|  | open-loop | 0.69 | 0.61 | 0.59 | 0.57 |
| URG | analysis | 0.70 | 0.61 | 0.59 | 0.57 |
|  | open-loop | 0.63 | 0.58 | 0.57 | 0.55 |
| CRD | analysis | 0.64 | 0.59 | 0.57 | 0.55 |
|  | open-loop | 0.61 | 0.55 | 0.51 | 0.49 |
| PRG | analysis | 0.62 | 0.56 | 0.51 | 0.49 |
|  | open-loop | 0.53 | 0.59 | 0.48 | 0.43 |
| CDM | analysis | 0.53 | 0.59 | 0.48 | 0.44 |
|  | open-loop | 0.59 | 0.48 | 0.38 | 0.41 |
| LHS | analysis | 0.60 | 0.48 | 0.38 | 0.40 |
|  | open-loop | 0.59 | 0.58 | 0.46 | 0.45 |
| SVN | analysis | 0.59 | 0.59 | 0.47 | 0.46 |
|  | open-loop | 0.63 | 0.54 | 0.46 | 0.39 |
| MNT | analysis | 0.63 | 0.54 | 0.47 | 0.39 |
|  | open-loop | 0.61 | 0.51 | 0.50 | 0.40 |
| SFL | analysis | 0.61 | 0.51 | 0.51 | 0.39 |
|  | open-loop | 0.44 | 0.46 | 0.44 | 0.38 |
| MTM | analysis | 0.44 | 0.46 | 0.44 | 0.38 |
|  | open-loop | 0.60 | 0.45 | 0.36 | 0.34 |
| LZC | analysis | 0.61 | 0.45 | 0.36 | 0.34 |
|  | open-loop | 0.60 | 0.56 | 0.52 | 0.55 |
| NBN | analysis | 0.60 | 0.56 | 0.52 | 0.54 |

## 4 Conclusions

This chapter focused on how the WCM is implemented in the SEKF in order to directly assimilate level 1 active radar backscatter $\left(\sigma^{\circ}\right)$ observations from C-band ASCAT sensors within the LDAS-Monde tool. In order to assess the efficiency of the assimilation, stastical scores between the analysis and openloop experiments were produced for the 12 SMOSMANIA stations located in southwestern France. The outcome of the calibration of WCM parameters using the SCE-UA optimization method were presented in Table IV.1. Results show that the WCM is able to fairly reproduce the ASCAT $\sigma^{\circ}$ observations, except for the MTM station which is located on a karstic area.

Assimilation results found over the different stations demonstrate that assimilating ASCAT $\sigma^{\circ}$ observations had a clear impact on the analysis. However, only minor improvements of SSM were achieved. When comparing openloop and analysis SSM and LAI simulations, it appeared that the assimilation had more impact on LAI than on SSM overall. The sensitivity of the WCM to LAI varied with soil moisture conditions and was reduced at intermediate SSM values. Therefore, the assimilation was more efficient in either markedly wet or dry conditions.

A limitation of this work was that parameters of the WCM were calibrated over the several annual cycles and not seasonally, so there may be seasons when the WCM fits less the observations than for other seasons. Shamambo et al. (2019) clearly elaborated that the WCM tends to perform poorly over straw cereals agricultural areas at springtime. Therefore, seasonal calibration of the WCM parameters in such areas could have further enhanced the impact of the assimilation, especially on LAI. This is the case of the LHS, CDM and PRG stations which are located in such agricultural areas. Further research could be conducted on defining the optimal observation error to be used when assimilating ASCAT $\sigma^{\circ}$ observations. The 0.33 dB observation error derived from Lievens et al. (2017a) was used but exploring other values could be interesting. Furthermore, maybe jointly assimilating ASCAT $\sigma^{\circ}$ observations with independent variables like LAI could improve the performance of the data assimilation system.

The capability of using LDAS-Monde to assimilate ASCAT $\sigma^{\circ}$ observations was demonstrated. These first results will serve as a useful benchmark for further research to be conducted so as to maximise the direct benefit of assimilating these observations in the ISBA LSM. In particular, a comparison of the performance of assimilating a Level 1 ASCAT $\sigma^{\circ}$ product instead of a Level 2 ASCAT SSM product could be made. Previous works at CNRM suggested that the assimilation of SSM has little impact on the soil-plant system state (Albergel et al. 2010).

## CHAPTER V - Prospects for future use of C-band radar observations

Remote sensing offers a great opportunity to monitor vegetation dynamics because of the availability of dataset on a global scale with improved spatial and temporal resolution (Billingsley 1984; Casa et al. 2018). Advances in the retrieval of remote sensing dataset related to vegetation dynamics has provided enormous capacity in crop monitoring. Numerous studies (Baret et al. 2007; Duchemin et al. 2006; Weiss et al. 2004) have used satellite observation from optical satellite observations at visible and near-infrared wavelengths to monitor crops. However, observations from optical sensors are limited to the fact they cannot assure continuity of crop monitoring in cloud conditions. On the other hand, the availability of C-band radar observations and the ensured continuity to have these datasets in nearly all-weather conditions offers a greater warrant to use these observations for various applications related to managing and monitoring the terrestrial ecosystems, particularly accurately accurately providing temporal information on crop growth status. Aquisitions of C-band dataset are achieved by sensors such as ASCAT, Sentinel-1, or RADARSAT-2, which provide active radar backscatter observations that have information related to the soil water content and vegetation dynamics. These data have so far been considered to monitor soil moisture but they could also be useful to monitor vegetation density together with ecophysiological variables related to plant growth processes.

## 1 Introduction

Observing the temporal evolution of the crop growth cycle is crucial for monitoring and predicting agricultural production. Enhancing the characterization of spatial and temporal vegetation dynamics for crop monitoring is needed (Moran et al. 1997; Inoue 2003; Doraiswamy et al. 2004). Improving crop yield and irrigation management is relevant for agricultural purposes and Earth observations from satellites bear great potential for accurately reinforcing the monitoring of vegetation dynamics over agricultural areas.

Microwave backscattering can detect the water stress of vegetation because it is related to the dielectric permittivity of the vegetation water content and to vegetation cover. Several studies (Cloutis 1999; Paloscia et al. 1999; Kurosu et al. 1995; Fieuzal et al. 2013; Inoue et al. 2014; Wigneron et al. 2007; Lawrence et al. 2014; El Hajj et al. 2019) have shown the potential of C-band sensors in monitoring vegetation dynamics over croplands. The possibility of getting radar vegetation retrievals such as vegetation optical depth (VOD) offers an alternative to LAI and to the traditional vegetation indices such as NDVI for monitoring vegetation. It is also possible to link these radar vegetation retrievals to other vegetation density indicators in order to obtain new products.

VOD at C-band and X-band is linked to leaf biomass and hence to LAI (Zribi et al. 2011, Momen et al. 2017, Vreugdenhil et al. 2017). Since VOD is related to leaf biomass rather than to leaf surface, the ratio of LAI to VOD can be expected to be related to the Specific Leaf Area (SLA). SLA has been proven to be a key variable of crop growth as it is related to leaf nitrogen and photosynthetic capacity variations (Gutschick and Wiegel 1988, Ali et al. 2015; Hussain et al. 2020). SLA is also a key parameter in LSMs. It is often assumed to be a constant value. In reality, SLA may present a seasonal cycle, especially over straw cereals such as wheat (Brisson and Casals, 2005). The SLA values may also change very rapidly (e.g. for wheat during the stem elongation phase). SLA may also present decadal and multi-decadal changes related to nitrogen supply and to the $\mathrm{CO}_{2}$ fertilization effect. Hence, VOD estimates could be used to complement existing LAI products and also to estimate SLA.

In the research work of Vreugdenhil et al. (2016), the potential of using ASCAT VOD to study vegetation dynamics was exploited and it was shown that the ASCAT VOD is able to capture the inter-annual variability of vegetation. VOD estimates can also be retrieved from the Sentinel-1 C-band SAR sensor using the Water Cloud Model (WCM) (Attema et al. 1978, Ulaby et al. 1986), as shown by El Hajj et al. (2019).

In this chapter, an assessment of the vegetation trends, particularly over straw cereal crops, is done using C-band VOD and LAI time series over southwestern France for year 2010.

## 2. Datasets

### 2.1 Vegetation Optical Depth (VOD)

In this chapter, C-band VOD estimates from the ASCAT radar backscatter observations are used. They were retrieved by TUWien (Vienna University of Technology, Austria) using the SSM retrieval algorithm (Wagner et al. 2013) and the WCM. In the WCM, the sum of the vegetation contribution and of the soil contribution attenuated by the vegetation equals the total backscatter coefficient (Eq. II.6). The two-way attenuation transmissivity from the vegetation contribution is expressed as in Eq. II.8. The $\mathrm{B} \times \mathrm{V}_{2}$ part of this equation is equivalent to VOD (Eq. II.10). Vreugdenhil et al. (2016) have shown that changes in total backscatter signal ( $\Delta \sigma_{\text {total }}^{0}$ ) and in the soil contribution ( $\Delta \sigma_{\text {soil }}^{0}$ ) can be used to estimate VOD. Equations II.6, II. 8 and II. 10 can be solved as:

$$
\begin{equation*}
V O D=\frac{\cos \theta}{2} \ln \frac{\Delta \sigma_{\text {soil }}^{0}}{\Delta \sigma_{\text {total }}^{0}} \tag{V.1}
\end{equation*}
$$

where $\theta$ is the backscatter incidence angle.
The VOD estimates used in this study were produced by TUWien according to the Vreugdenhil method and were provided by TU-Wien. The VOD values were then extracted for straw cereal croplands over southwestern France from January to December 2010.

### 2.2 LAI Observations

The true Leaf Area Index (LAI) GEOV2 produced by the Copernicus Global Land Service (CGLS) (http://land.copernicus.eu/global/) as detailed in section 1.2 of Chapter II is used for the investigations made in this chapter. Like its prior version (GEOV1) LAI GEOV2 has a frequency of 10 days, however, for this study, a linear interpolation was applied to the LAI observations in order to have LAI values on a daily basis.

## 3. Results and discussion

### 3.1. Time series analysis

Vegetation geophysical variables such as LAI and VOD are essential for monitoring crop phenology. Results showing temporal evolution of VOD and LAI for a straw cereal area are displayed in Figure V. 1 together with the LAI/VOD ratio. The VOD increases from January to the end of spring. It reaches its peak on 28 May 2010. The period during the increase of the VOD values correspond to the growing phase of the crops. After the growing season, a decrease in VOD values can be observed. This phase is representative of the senescence period over this region (see for example Zhang et al. 2017). During the senescence period, there is a decrease in vegetation water content (VWC) of straw cereals which can explains why VOD values decrease because VOD is a direct proxy for VWC.

As for the LAI timeseries on Figure V.1, the LAI peak is observed on 10 May 2010. The LAI values peak earlier than VOD by about 18 days. The lag between LAI and VOD over straw cereals can be somehow explained by the different vegetation features depicted by the two datasets. VOD is sensitive to VWC while LAI is more related to the vegetation photosynthetic activity. Hence differences between the two products are expected. The changes in VOD observed in this work are consistent with other research studies. For example Wigneron et al. (1999), Patton and Hornbuckle (2012) and Togliatti (2020) used VOD products to monitor crops and their distinctive studies showed that the VWC of crops varies from minimum to maximum at the highest reproduction phase of the plant and then back to the mimimum during senescence. Vreugdenhil et al. (2017) used LAI GEOV1 and ASCAT VOD to assess the vegetation dynamics over mainland Australia. They showed similar findings where VOD lagged behind LAI over croplands. In Lawrence et al. (2014), a difference of about 19 days was observed when VOD estimated from SMOS (L-band) and MODIS LAI were compared over crops in the USA. When compared to other vegetation geophysical indices such as NDVI, it was found (El Hajj et al. 2019) that VOD values peak earlier than NDVI.

Figure V. 1 also shows the temporal evolution of the ratio of LAI to VOD (LAI/VOD). It is observed that LAI/VOD has its highest value on 1 May 2020, 9 days before the peak of LAI. Despite this difference, LAI/VOD and LAI phenological evolution over straw cereal areas are similar. Since the ratio of LAI to VOD may corresponds to the specific leaf area (SLA), this new product (LAI/VOD) determined by variables that are retrieved from satellite observations can be useful for the prediction of SLA. SLA is a key variable of plant growth as it determines the distribution of plant biomass relative to leaf area within a plant canopy (Pierce et al. 1994; Kimball et al. 2002). A number of studies have already illustrated the role that SLA plays in linking plant carbon and water cycles (Liu et al. 2017; Cornelissen et al. 2003; Pierce et al. 1994).

Brisson and Casals (2005) showed that SLA has similar phenological evolution as LAI over a wheat crop. This SLA behavior is consistent with the LAI/VOD timeseries in Figure V.1. SLA dynamics exhibits successive increasing and decreasing phases (Brisson and Casals 2005) which are representative of the growing and senescence phase of the crops.

Since it is assumed in this work that VOD $=B \times$ LAI (Eq. II.10), the inverse of the $B$ parameter of the WCM is related to SLA: $1 / B=\mathrm{LAI} / \mathrm{VOD}$. Assuming that $B$ has a constant value is probably wrong over straw cereals.
(a)

(b)

(c)


Figure V. 1 - Temporal evolution of (a) VOD, (b) LAI and (c) the ratio of LAI to VOD (LAI/VOD) for year 2010 over a straw cereal crop area in southwestern France close to the Lomagne area in Figure 1 of Shamambo et al. (2019).
(a)

(b)


Figure V. 2 - Hysteresis in the LAI/VOD vs. LAI relationship for straw cereal areas: schematic representations of (a) LAI and VOD temporal evolution (x-axis represents time) and (b) the relationship between LAI/VOD and LAI from (1) leaf onset to (2) peak LAI and to (3) senescence.


Figure V. 3 - Hysteresis in the LAI/VOD vs. LAI relationship for straw cereal areas: satellite-derived observations for April, May and June 2010 over a straw cereal crop area in southwestern France close to the Lomagne area in Figure 1 of Shamambo et al. (2019).

### 3.2 Relationship between LAI/VOD and LAI for straw cereals

A detailed assessment of the relationship between LAI/VOD and LAI was made for the growing and senescence period over a straw ceral area close to Lomagne (see Figure 1 in Shamambo et al. 2019) in southwestern France. The analysis was made for the year 2010 and months of April, March and June were considered as wheat growth and senescence usually occur during this period in southwestern France.

Considering the temporal shifts of LAI and VOD, Figure V. 2 illustrates how the temporal evolution of the two datasets can be depicted on the same scatterplot. When LAI/VOD is plotted as a function of LAI, a hysteresis behavior is to be expected because of the temporal shift between LAI and VOD. For the same value of LAI before and after the senescence, two distinct LAI/VOD values are observed, the former being larger than the latter. From Figure V. 2 we see that at the peak of LAI, the growth period is immediately followed by senescence period. This is represented by notation (2) on subfigures (a) and (b)), (1) corresponds to the start of the growth period and (3) to the end of the senescence.

The same LAI/VOD vs. LAI plot is presented in Figure V. 3 using the observations of Figure V.1. It is observed that the relationship between LAI/VOD and LAI presents two successive phases, the growing period (in dark green Figure V.3) and the senescence period (in pale green). The same hysteresis behavior as in Figure V. 2 is observed. The asymptotic LAI and LAI/VOD values corresponding to label (2) in Figure V. 2 are $3.5 \mathrm{~m}^{2} \mathrm{~m}^{-2}$ and 11.6, respectively. For each period (growing period and senescence period), a linear regression was carried out between LAI/VOD and LAI. As shown in Figure V.3, two relationships are found for the growing period and for the senescence period, respectively:

LAI $/ \mathrm{VOD}=0.95+3.00 \times$ LAI $(R=0.95, \mathrm{P}<0.001)$
$\mathrm{LAI} / \mathrm{VOD}=-0.01+3.27 \times \mathrm{LAI}(\mathrm{R}=0.95, \mathrm{P}<0.001)$
Since LAI/VOD is related to SLA, it also implies that the relationship between SLA and LAI will probably have the same behavior as that of LAI/VOD and LAI during the growth and senescence periods. Similar findings were reported in other research work. For example, Pierce et al. (1994) showed that SLA is significantly correlated to LAI.

## 4. Conclusions

In this chapter, an evaluation of the ASCAT C-band radar VOD product for a straw cereal agricultural area in southwestern France was carried out. The objective was to assess the hypothesis VOD $=B \times$ LAI of the version of the WCM used in this work because it was shown in Shamambo et al. (2019) that assuming a constant value of the $B$ parameter is probably wrong for straw cereals. The seasonal cycle of VOD was investigated and compared to the seasonal cycle of LAI. Retrieved VOD values provided by TUWien were found to increase during the growing season and then decrease during the senescence, like LAI but with a lag of two to three weeks. This lag can be explained by the different
vegetation characteristic patterns represented by the two products. VOD is directly related to water held in vegetation while true LAI is related to the green leaf surface. The analysis of the ratio between LAI and VOD (LAI/VOD) showed that this ratio has a similar seasonal evolution as LAI. LAI/VOD correlates very well with LAI for either growing or senescence periods. Two distinct linear relation ships are found for the growing period and for the senescence, indicating a hysteresis in the relation ship between LAI/VOD and LAI. This finding implies that the relationship between LAI/VOD and LAI can provide information on plant phenology in relationship to photosynthetic capacity. These results are similar to the comparative analysis made between LAI timeseries and SLA timeseries for a wheat crop by Brisson and Casals (2005). This similarity between LAI/VOD and SLA demonstrates that SLA seasonal changes could be inferred from LAI/VOD observations. SLA plays a role in linking plant water and carbon fluxes, and being able to retrieve a proxy for SLA from satellite observations is important for monitoring crops and ecosystems.

## CHAPTER VI - Conclusions et perspectives

Cette thèse a été réalisée dans le cadre scientifique offert par l'initiative HyMex (https://www.hymex.org/). HyMex a pour objectif de mieux décrire les interactions entre l'hydrologie continentale, l'atmosphère, et la mer Méditerranée. La possibilité d'intégrer des données satellitaires dans le modèle ISBA des surfaces terrestres est susceptible d'améliorer la representation des variables de surface à partir des simulations réalisées par le modèle. Ce travail a porté essentiellement sur l'assimilation directe dans ISBA des coefficients de rétrodiffusion radar en bande $\mathrm{C}\left(\sigma^{\circ}\right)$ mesurés par les instruments ASCAT en utilisant l'outil d'assimilation à l'échelle mondiale LDAS-Monde. La disponibilité des observations radar en bande C, leur continuité assurée grâce aux programmes spatiaux européens, et leur capacité à observer les surfaces par tout temps, sont des atouts considérables. D'autre part, une résolution spatiale améliorée est maintenant atteignable grâce à Sentinel-1. L'utilisation de telles observations offre l'opportunité de progresser dans le contexte scientifique d'HyMex.

La première phase de ce travail de thèse a consisté à concevoir un opérateur d'observation qui soit capable de représenter les observations de $\sigma^{\circ}$ ASCAT à partir de variables simulées par ISBA sur la zone Euro-Méditerranée. Dans toutes les expériences numériques réalisées dans ce travail, les conditions de gel du sol ont été filtrées ainsi que les zones situées à plus de 1200 m d'altitude, afin déviter qu'elles n'affectent l'interprétation des $\sigma^{\circ}$ observés et simulés. Le «water cloud model» (WCM) a été utilisé comme modèle de transfert radiatif pour relier les variables simulées par ISBA avec les observations de $\sigma^{\circ}$ ASCAT. Le WCM a été alimenté avec des observations d'indice foliaire de la végétation (LAI) provenant de CGLS et avec l'humidité superficielle du sol simulée par ISBA, afin de caler ses paramètres. Le LAI ISBA n'a pas été utilisé dans la phase de calage car les résultats obtenus en termes de paramètres $A, B, C$, et $D$ du WCM étaient moins bons. Le calage de ces paramètres statiques du WCM caractérisant les propriétés du sol et de la végétation a été réalisé en utilisant la méthode «Shuffled Complex Evolution Model Calibrating Algorithm » (SCE-UA). Cette méthode a fourni des estimations des valeurs des paramètres du WCM dont la robustesse a été vérifiée. Plusieurs approches pour le calage des paramètres ont été testées. La meilleure approche a consisté à caler les quatre paramètres en même temps. De meilleurs scores statistiques ont ainsi été obtenus pour les $\sigma^{\circ}$ ainsi qu'une répartition statistique plus réaliste des valeurs des paramètres.

L'analyse des résultats sur la zone Euro-Méditerranée a montré que le WCM peut être utilisé pour simuler les $\sigma^{\circ}$ ASCAT dans des conditions climatiques et d'occupation du sol très variées. En général, de bonnes corrélations ont été trouvées entre les $\sigma^{\circ}$ simulés et les $\sigma^{\circ}$ ASCAT. Cependant, des corrélations faibles voire négatives ont été observées dans le cas des zones calcaires de type karstique, mal représentées à la fois par le WCM et par ISBA. L'analyse des biais de $\sigma^{\circ}$ du modèle a montré que les zones agricoles comportant une part importante de surfaces en blé présentent un biais saisonnier, négatif au printemps (sousestimation des $\sigma^{\circ}$ par le modèle) et positif en été. Dans l'ensemble, les anomalies
mensuelles des $\sigma^{\circ}$ simulés étaient cohérentes avec les anomalies des $\sigma^{\circ}$ ASCAT. Il a été montré que les $\sigma^{\circ}$ ASCAT ont tendance à augmenter au cours du temps et cette tendance n'est pas expliquée par le modèle.

L'analyse de la réponse des $\sigma^{\circ}$ au LAI et à l'humidité superficielle du sol a montré des résultats contrastés selon la zone considérée. Une analyse plus poussée a été réalisée sur le sud-ouest de la France et a été publiée (Shamambo et al. 2019). Il a été possible de confirmer que le WCM présente des biais saisonniers sur les surfaces agricoles dominées par les céréales à paille telles que le blé. Sur ces surfaces, un calage saisonnier du paramètre $B$ du WCM a permis de réduire le biais. Ce paramètre est égal au rapport entre l'épaisseur optique micro-ondes de la végétation (ou «VOD» en anglais) et le LAI. Il semble être relié à la surface foliaire spécifique (ou «SLA» en anglais). Ce facteur peut présenter des variations rapides pour le blé lors de la phase d'élongation des tiges.

Le rapport entre le LAI et le VOD a été examiné sur les zones agricoles du sud-ouest de la France dominées par les céréales à paille. Il a été montré que l'évolution au cours du temps du rapport LAI/VOD est semblable à celle du LAI, avec un décalage de deux à trois semaines du pic de VOD par rapport au pic de LAI. Cette évolution temporelle de LAI/VOD est similaire à celle observée pour le SLA sur les couverts de blé telle qu'on peut la trouver dans la littérature scientifique. La possibilité d'estimer le SLA en utilisant des observations satellitaires de LAI et de VOD est un résultat intéressant étant donné l'importance du SLA en modélisation de la physiologie des plantes.

Une autre étude visant à évaluer l'impact de la végétation sur le signal a porté sur l'impact d'un changement rapide de couvert végétal sur le signal $\sigma^{\circ}$. Pour cela, les dégâts forestiers causés par la tempête Klaus de janvier 2009 dans la forêt des Landes ont été utilisés. On montre que les $\sigma^{\circ}$ simulés par le WCM sont capables de détecter le changement de végétation forestière au même titre que les $\sigma^{\circ}$ ASCAT. La différence de $\sigma^{\circ}$ entre la zone forestière la plus affectée par Klaus et les zones agricoles voisines est modifiée après la tempête et cela peut être expliqué par les valeurs plus faibles de LAI de la forêt. En revanche, les changements occasionnés par la phase de régénération de la forêt, à partir de 2013, ne peuvent être expliqués que par un accroissement de la valeur du paramètre $B$ du WCM. Une explication de ce phénomène est la présence d'arbres plus jeunes.

La mise en oeuvre du WCM sur la zone Euro-Méditerranée et sur le sud-ouest de la France ayant été réalisée avec succès, l'étape suivante a consisté à créer un opérateur d'observation fondé sur le WCM afin d'assimiler les observations $\sigma^{\circ}$ ASCAT dans le modèle ISBA.

Les expériences d'assimilation ont été conduites à l'aplomb de 12 stations du réseau SMOSMANIA de mesure de l'humidité des sols dans le sud-ouest de la France. Dans un premier temps, la mise en œuvre du WCM dans le filtre de Kalman simplifié étendu (SEKF) a été réalisée. L'étude de la sensibilité du modèle en utilisant les Jacobiens de l'opérateur d'observation a montré que l'assimilation des $\sigma^{\circ}$ ASCAT a un impact sur toutes les variables de contrôle du modèle ISBA. En revanche, il a été observé que l'impact de l'assimilation des $\sigma^{\circ}$ ASCAT n'est pas le même pour toutes les variables de contrôle reliées à l'humidité du sol. L'efficacité de l'assimilation des $\sigma^{\circ}$ ASCAT pour mieux estimer l'humidité du sol varie d'une couche de sol à une autre en fonction des saisons. Les incréments d'analyse ont
également montré une variabilité saisonnière pour toutes les variables de contrôle. En général, l'assimilation des $\sigma^{\circ} \mathrm{ASCAT}$ a eu pour conséquence d'augmenter légèrement le LAI simulé en mars et en septembre et de le diminuer en juillet. Des résultats assez différents ont été obtenus pour la station de MTM qui est localisée sur une zone karstique. Dans l'ensemble, on peut considérer que la faisabilité d'assimiler les $\sigma^{\circ}$ ASCAT dans le modèle ISBA en utilisant l'outil LDAS-Monde a été démontrée. Ces premiers résultats ont montré que l'assimilation a un impact neutre à modérément positif sur toutes les variables.

A la suite de ce travail de thèse, une étape supplémentaire pourrait être d'améliorer la matrice de covariance d'erreur des observations $\sigma^{\circ}$ ASCAT. Une représentation plus fine des erreurs affectant les $\sigma^{\circ}$ ASCAT pourrait améliorer la performance du système d'assimilation. D'autre part, une variabilité saisonnière des paramètres du WCM pourrait être considérée pour certains types d'occupation des sols, notamment les zones agricoles dominées par les céréales à paille. Cela permettrait de réduire les biais saisonniers. L'assimilation conjointe des $\sigma^{\circ}$ ASCAT avec d'autres produits satellitaires tels que le LAI vrai pourrait également améliorer l'efficacité de LDAS-Monde. Le WCM et l'assimilation des $\sigma^{\circ}$ pourraient enfin être mis en œuvre à l'échelle mondiale. Dans le même temps, l'assimilation à des échelles plus fines d'observations de $\sigma^{\circ}$ provenant de Sentinel-1 pourrait être envisagée.

La plupart des études publiées d'assimilation de données utilisent des produits satellitaires de niveau 2 issus d'algorithmes de restitution. Il s'agit par exemple de produits d'humidité superficielle du sol, ou d'indice de surface foliaire de la végétation. Cependant, ces algorithmes sont susceptibles d'utiliser des paramètres des surfaces terrestres et des sources d'information géographique qui pourraient ne pas être en cohérence avec les simulations des modèles. D'autre part, lorsque les restitutions et les simulations utilisent la même information géographique, cela peut générer des erreurs de corrélation croisée. En revanche, l'assimilation directe de produits de niveau 1 tels que les $\sigma^{0}$ radar a l'avantage de ne pas dépendre de données auxiliaires qui soient cohérentes entre modèle et observations. Cela évite les erreurs de corrélation croisée. Ce travail de thèse est une première étape de demonstration de la faisabilité d'utiliser un opérateur d'observation pour assimiler des produits de niveau 1 dans le modèle ISBA. Il pourrait être étendu à d'autres types de données de niveau 1. D'autre part, plutôt que d'utiliser des modèles semi-empiriques tels que le WCM, il pourrait être envisagé d'utiliser des modèles statistiques fondés sur l'apprentissage automatique.

Le suivi des cultures pourrait être amélioré grâce à l'utilisation d'observations de télédétection spatiale provenant de radars en bande C telles que ASCAT ou Sentinel-1 car ils fournissent des coefficients de rétrodiffusion qui contiennent de l'information à la fois sur l'humidité superficielle du sol et sur la dynamique de la végétation. D'autre part, les observations en bande C sont disponibles fréquemment et par tout temps. Un projet de mission spatiale en orbite géosynchrone tel que Hydroterra « Earth Explorer » (Hobbs et al. 2019) permettrait d'accroître la fréquence de telles observations sur des zones à enjeu climatique de la zone Euro-Méditerranée et en Afrique.

## CHAPTER VII - Conclusions and prospects

This thesis was conducted under the framework of the HyMex project (https://www.hymex.org/). HyMex aims to better describe the interactions between the continental hydrology, atmosphere and the Mediterranean Sea in order to improve the understanding and modeling of the water cycle in the Mediterranean area. The possibility of integrating satellite observations into the ISBA LSM can improve the representation of land surface variables from model simulations. This work focused on directly assimilating ASCAT radar C-band backscatter observations into ISBA using the global LDAS-Monde data assimilation tool. The availability of C-band radar observations and the ensured continuity of such datasets that are able to observe land surfaces in nearly all-weather conditions through European space programmes are key assets. Moreover, enhanced spatial resolution is now possible thanks to Sentinel-1. Using such observations is a great opportunity to progress in the HyMex scientific context.

The first phase of this PhD work consisted of designing an observation operator that was capable of representing the ASCAT $\sigma^{\circ}$ observations from the ISBA simulated variables over the Euro-Mediterranean area. Over all the experiments carried out in this study, soil freezing conditions and topography above 1200 m above sea level were masked out in order to prevent these conditions from affecting either the observed or the simulated $\sigma^{\circ}$. The water cloud model (WCM) was retained as the radiative transfer model capable of linking ISBA simulated variables to the ASCAT $\sigma^{\circ}$ observations. The WCM was supplied with satellitederived true leaf area index (LAI) observations from the CGLS and with surface soil moisture from ISBA as initial variables needed to calibrate its parameters. It was found that calibrating the WCM model with the CGLS LAI presented better outcomes of the $A, B, C$ and $D$ WCM parameters than using LAI simulated by ISBA. In order to calibrate the WCM parameters describing static soil and vegetation characteristics, the Shuffled Complex Evolution Model Calibrating Algorithm (SCE-UA) was implemented and this method provided robust estimates of the WCM parameter values. Several approaches for calibrating the WCM model were tested. The approach consisting in fitting all parameters at once was found to be the best choice as it presented better $\sigma^{\circ}$ statistical scores and a more realistic statistical distribution of the parameter values.

Analysis over the Euro-Mediterranean area showed that the WCM can be used to simulate ASCAT $\sigma^{\circ}$ observations under contrasting climate and land surface conditions. Generally good correlation results were found between simulated $\sigma^{\circ}$ and ASCAT $\sigma^{\circ}$ observations. However, poor correlation values were observed over calcareous karstic areas over which both the WCM and the ISBA LSM may have shortcomings. When seasonal average bias maps were displayed, zones with wheat croplands showed negative bias at springtime whilst during the summer, a positive bias was recorded. Overall, the monthly anomalies of simulated $\sigma^{\circ}$ were consistent with those of ASCAT $\sigma^{\circ}$ and this showed the skill of the WCM in modelling the temporal dynamics of ASCAT $\sigma^{\circ}$ observations. It was
discovered that the ASCAT $\sigma^{\circ}$ observations tended to increase with time and this trend could not be explained by the model.

Analysis made to understand the response of $\sigma^{\circ}$ to LAI and surface soil moisture showed varying results depending on the area investigated. A detailed analysis was performed over southwestern France and was published (Shamambo et al. 2019). It was found that the WCM presented a seasonal bias over agricultural areas dominated by straw cereals such as wheat. Over such areas, performing a seasonal calibration of the $B$ parameter of the WCM helped reducing the bias. This parameter is equal to the ratio of the microwave vegetation optical depth (VOD) to LAI and seemed to be related to the plant specific leaf area (SLA). The latter can present rapid changes for wheat during the stem elongation phase.

The ratio of LAI to VOD was investigated over agricultural areas in southwestern France dominated by straw cereals such as wheat. It was showed that the temporal evolution of the LAI/VOD ratio was similar to the evolution of LAI in relation to a time lag of two to three weeks of the VOD peak with respect to the LAI peak. The temporal evolution of LAI/VOD was found to be similar to that of SLA as described over wheat crops in the litterature. The possibility of estimating SLA using LAI and VOD satellite observations is an interesting finding given the importance of the SLA variable in plant physiology modelling.

Further analysis aimed at evaluating the impact of a rapid change in land use on the $\sigma^{\circ}$ signal using the Klaus storm event of January 2009 in the Landes forest. It was found that the WCM $\sigma^{\circ}$ simulations were able to detect the forest vegetation changes as seen in the ASCAT $\sigma^{\circ}$ observations. The difference in $\sigma^{\circ}$ between the zone affected by the storm and neighboring agricultural areas changed after the storm and this was explained by the reduced LAI values in the degraded forest area. On the other hand, changes associated with the forest regeneration phase starting in 2013 could only be explained by an increase of the $B$ parameter of the WCM, in relation to the presence of younger trees.

After the application of the WCM over the Euro-Mediterranean area and over southwestern France, it was concluded that the WCM could be used as an observation operator in the context of assimilating ASCAT $\sigma^{\circ}$ observations into the ISBA LSM.

Assimilation experiments were conducted over the 12 SMOSMANIA stations in southwestern France for which in situ soil moisture observations were available. The implementation of the WCM in the simplified extended Kalman filter (SEKF) was successfully achieved. Model sensitivity studies using the Jacobian of the observation operator showed that the assimilation of $\sigma^{\circ}$ impacted all control variables of the ISBA model. The impact of assimilating of ASCAT $\sigma^{\circ}$ was not the same for all control variables related to soil moisture. The efficiency of assimilating ASCAT $\sigma^{\circ}$ to predict better soil moisture estimates varied from one soil layer to another across seasons. Analysis increments varied as well from one season to another for all control variables. The assimilation of $\sigma^{\circ}$ generally tended to slightly increase LAI values in March and September and to decrease them in July. Rather different results were found for the MTM station which is located on a karstic area. Overall, the feasibility of assimilating ASCAT $\sigma^{\circ}$ observations into the ISBA

LSM using LDAS-Monde was demonstrated and these preliminary results showed that the assimilation had a neutral to positive impact on all variables.

Some next steps in the data assimilation research area could be finding an optimal observation error covariance matrix. More specific work needs to be realized focusing on finding the best optimal magnitude of the errors concerning the ASCAT $\sigma^{\circ}$ observations. This might lead to increased skill of the assimilation system. Besides that, seasonal estimation of the WCM parameters could be considered over specific land cover classes such as straw cereals in order to reduce seasonal biases. Furthermore, jointly assimilating $\sigma^{\circ}$ observations with other variables like true LAI could probably enhance the estimation of state variables and consequently improve the efficiency of LDAS-Monde. The WCM could be extended globally in order to allow the assimilation of $\sigma^{\circ}$ on a global scale. At the same time, the assimilation of finer spatial resolution $\sigma^{\circ}$ observations from Sentinel-1 could be investigated.

Most data assimilation studies over land make use of satellite observations retrievals (level 2 dataset) such as surface soil moisture, leaf area index. However, these retrieval products may use land surface parameters and auxiliary information that might led to inconsistencies with the model simulations. In addition, errors of cross-correlation can occur because both retrievals and model simulations depend on similar types of auxiliary information. On the other hand, directly assimilating level- 1 observations such as radar $\sigma^{0}$ observations has advantages because it does not need consistent parameter and auxiliary inputs between the model and observations, hence avoiding cross-correlated errors. This work is a first demonstration of the use of an observation operator to assimilate level-1 products in the ISBA model. It could be extended to other types of level- 1 observations. Moreover, rather than using semi-empirical models such as the WCM, one could envisage using statistical models based on machine learning techniques.

Monitoring of crops can be improved through the use of remote sensing observations from C-band radars like ASCAT or Sentinel-1 because they provide provide radar backscatter containing information on both surface soil moisture and vegetation dynamics. Furthermore, the C-band observations are available on a frequent basis and under allweather conditions. A new geosynchroneous satellite mission project like the Hydroterra Earth explorer for water cycle science (Hobbs et al. 2019) could help increase the frequency of such observations over climate hop-spots in the Euro-Mediterranean area and in Africa.

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