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EXECUTIVE SUMMARY

Eight different user-studies were chosen to investigate the potential value of new Aerosol_cci data products for the climate community in data applications. More specifically, in these user case studies (1) aerosol schemes in global models were evaluated (section 8), (2) data were applied in assimilations to demonstrate their impact of improved (aerosol) forecasts (section 7), (3) spatially and temporally associated aerosol and cloud property retrievals were combined to establish observational constrain to evaluate and to identify deficiencies in (aerosol- cloud) processing in global modeling (sections 5 and 10) and finally (4) aerosol retrieval data were applied in radiative transfer modeling to determine associated impacts on climate (section 4).

One of the major goals of ESA’s Aerosol_cci efforts was to establish long-term climate data records. This was achieved for ATSR (17 years), UV-AI (Aerosol index, 35-years) and IASI (10 years). These records and their capabilities to derive trends are discussed in sections 3 (AOD trends), 6 (AAI record) and 9 (coarse mode AOD trends). While these long-term records are capable of revealing spatial and temporal anomalies, the derivation of temporal trends with these datasets turned out to be rather difficult due to the (still) limited length of the data record and also in the context of retrieval accuracy limitations. The ATSR records suffers from inconsistencies between ATSR-2 and AATSR, which appear too large for trend applications of the combined record - especially for fine mode AOD (AODf) and coarse mode AOD (AODc) sub-components of total AOD. The UV-AI suffers from interpretation issues as both altitude and absorption (and here wildfire strength, or wildfire/dust ratio) complicate interpretation - so that trends analysis is most promising over regions with major wildfires. Part of the difficulty to retrieve global trends is also that the global annual average AOD (the main aerosol property retrieved by satellites) has not changed significantly over the last 30 years, despite strong regional variability.

Section 11 gives a summary of the highlights detected with the user case studies. The appendix provides images of seasonal anomalies.

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1 DEFINITIONS AND ABBREVIATIONS

This section summarizes the major definitions relevant for the validation report.

**AAOD** (Absorption Aerosol Optical Depth) is the vertically normalized atmospheric column integrated aerosol absorption at a certain wavelength (usually at 550 nm, the reference wavelength in global modelling) [note, AAOD = AOD*(1-SSA)]

**AeroCom** is an open science initiative founded to inter-compare aerosol modules in global modelling and evaluate overall model performance as well as the treatment of specific aerosol processes against available (and trusted) observations.

**AERONET** represents a federated network of globally distributed ground-based CIMEL sun-/sky-photometers, which is maintained (calibration facility, data processing and aerosol and water vapor products access) by NASA (National Aeronautics and Space Administration) and PHOTONS (PHOtométrie pour le Traitement Opérationnel de Normalisation Satellitaire)

**AOD** (Aerosol Optical Depth) is the vertically normalized atmospheric column integrated aerosol extinction at a certain wavelength or waveband (usually at 550nm, the reference wavelength in modelling). AOD is also often referred to as Aerosol Optical Thickness (AOT).

**AODf** (Fine-mode Aerosol Optical Depth) is the vertically normalized atmospheric column integrated aerosol extinction at a certain wavelength or waveband (usually at 550nm) of aerosol particles smaller than 0.5um in radius (or smaller 1um in diameter).

**AODc** (Coarse-mode Aerosol Optical Depth) is the vertically normalized atmospheric column integrated aerosol extinction at a certain wavelength or waveband (usually at 550nm) of aerosol particles larger than 0.5um in radius (or larger 1um in diameter)

**ATSR** (Along Track Scanning Radiometer) was a multi-channel imaging radiometer (with dual view capabilities in the visible and near-IR solar spectrum). Two versions are used for aerosol retrieval: ATSR-2 on board of the European Space Agency’s ERS-2 satellite (1995-2002) and the advanced ATSR (AATSR) on ESA’s ENVISAT satellite (2002-2012).

**CALIOP** (Cloud-Aerosol Lidar with Orthogonal Polarization) is a two-wavelength polarization-sensitive backscatter lidar that provides high-resolution vertical profiles of aerosols and clouds onboard NASA’s CALIPSO satellite.

**CCM** (Chemistry Climate Model) is a global atmospheric circulation model with interactive chemistry.

**CF** (Climate and Forecast) naming convention metadata are designed to promote the processing and sharing of files created with the NetCDF API.

**CMUG** (Climate Model User Group) is a part of ESA’s Climate Change Initiative (CCI) and is composed of members of major climate research institutes in Europe. The group is tasked to oversee the usefulness of new climate data records produced for CCI selected ECVs.

**ECV** (Essential Climate Variables) are geo-physical quantities of the Earth-Atmosphere-System that are technically and economically feasible for systematic (climate) observations.

**EMAC** (ECHAM5/MESSy Atmospheric Chemistry) is a modular chemistry climate model.
VENISAT ("Environmental Satellite") is a now inoperative ESA polar-orbiting (ca 10am local overpass) satellite, which supplied between 2002 and 2012 atmospheric data, including for aerosol remote sensing relevant AATSR, MERIS and GOMOS sensor data.

ESA (European Space Agency) is the European Organisation for Space Research with Headquarters in Paris.

FCDR (Fundamental Climate Data Records or simply CDR) represent long-term records of measurements or retrieved physical quantities from remote sensing. FCDRs require consistency across multiple platforms with respect to (1) calibration, (2) algorithms, (3) spatial and temporal resolution, (4) quantification of errors and biases and (5) data format. FCDRs also need to manifest applied ancillary data.

FMF (Fine Mode Fraction) is the fraction of the total AOD which is contributed by aerosol particles smaller than 1um in diameter. Due to their smaller size these aerosol particles are referred to as fine-mode aerosol, in contrast to (larger or) coarse mode aerosol particles.

GCOS (Global Climate Observing System), located at WMO in Geneve, is intended to be a long-term, user-driven operational system capable of providing the comprehensive observations required for (1) monitoring the climate system, (2) detecting and attributing climate change, (3) assessing impacts of, and supporting adaptation to, climate variability and change, (4) application to national economic development and (5) research to improve understanding, modelling and prediction of the climate system.

GRASP (Generalized Retrieval of Aerosol and Surface Properties) is an aerosol retrieval algorithm that processes properties of aerosol- and land-surface-reflectance. It infers nearly 50 aerosol and surface parameters including particle size distribution, the spectral index of refraction, the degree of sphericity and absorption.

GOMOS (Global Ozone Monitoring by Occultation of Stars) is an instrument on board the European satellite ENVISAT. The main scientific objective of this stellar occultation instrument is to monitor ozone and ozone trends as function of altitude in the upper atmosphere (stratosphere, mesosphere). GOMOS also measures atmospheric parameters related to (stratospheric ozone) chemistry like NO2, NO3, H2O and aerosol as well as ozone dynamics like temperature, air density and turbulence.

IASI (Infrared Atmospheric Sounding Interferometer) on European MetOp platforms senses the thermal heat emission from the Earth (with a Michelson interferometer) mainly to provide atmospheric temperature and humidity profiles.

ICAP (International Cooperative for Aerosol Prediction) is an international forum for aerosol forecast centers, remote sensing data providers, and lead systems developers to share best practices and discuss pressing issues facing the operational aerosol community.

MACC (Monitoring Atmospheric Composition and Climate) were EU-funded projects for the development of a chemical weather forecast service. Now in its operational phase, Copernicus predicts global distributions and long-range transports of greenhouse gases (carbon dioxide, methane), of aerosols that result from both natural processes and human activities and of reactive gases (tropospheric ozone, nitrogen dioxide). Copernicus also evaluates how these constituents influence climate and estimates their sources and sinks.

MAN (Marine Aerosol Network) is the ocean branch of the AERONET network, based on handheld solar attenuation measurements with calibrated MICROTOPS-II sun-photometers.

MERIS (Medium Resolution Imaging Spectrometer) was a solar spectral satellite sensor on ESA’s ENVISAT platform.
MISR (Multi-angle Imaging Spectro-Radiometer) is a multi-spectral sensor on NASA’s EOS Terra platform with (9) multi-directional view capabilities.

MODIS (Moderate Resolution Imaging Spectro-Radiometer) is a multi-spectral sensor on NASA’s EOS Terra and Aqua platforms.

NASA (National Aeronautics and Space Administration), deutsch ist die 1958 gegründete zivile US-Bundesbehörde für Raumfahrt und Flugwissenschaft. Der Hauptsitz befindet sich in Washington, D.C.

OMI (Ozone Monitoring Instrument) is a UV multi-spectral sensor on NASA’s EOS Aura platform.

POLDER (POLarization and Directionality of the Earth's Reflectances) is a passive optical imaging radiometer and polarimeter for studies on radiative and microphysical properties of clouds and aerosols on the French CNES PARASOL (Polarization and Anisotropy of Reflectances for Atmospheric Sciences coupled with Observations from a Lidar).

SEAWIFS (Sea-viewing Wide Field-of-view Sensor) was the sensor on the US GeoEye-Satellits Orb-View-2 (SeaStar).

SCIAMACHY (Scanning Imaging Absorption Spectrometer for Atmospheric ChartographY) was a high spectral resolution passive sensor (in the UV and the visible solar spectral region) with both nadir and limb measurement capabilities on the ESA’s ENVISAT platform.

SLTSR (Sea and Land Surface Temperature Radiometer) on-board SENTINEL-3 is to maintain continuity with the (A)ATSR series of instruments. Additional new features include a wider swath, new channels (including two channels dedicated to fire detection), and higher resolution in some channels.

SSA (Single Scattering Albedo) quantifies the likelihood of scattering during an attenuation (or 'extinction') event by an atmospheric particle of given size and shape at a certain wavelength (most important at 550 nm, the reference wavelength in global modeling). The remaining fraction, 1-SSA referred to co-single scattering albedo, quantifies the likelihood of absorption during an attenuation (or extinction) event.

SYNERG (Synergistic observations from AATSR and MERIS) is a multi-sensor retrieval developed at DLR
2 INTRODUCTION

Half a decade ago ESA’s Aerosolcci set out to develop and improve aerosol retrievals for European satellite sensors. These new products permitted new science studies. In order to demonstrate useful applications selected ‘user-case’ studies were supported. The results of these user case studies are summarized in this document. The titles (shortened) and the associated chapters are summarized in Table 2.1.

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One of the major goals of ESA’s Aerosolcci effort was to establish long-term climate data records to offer long-term climate data in parallel to model simulations to assist in model evaluations. In that context one task of one option was to compile the UV-AI data record and compare the record to modeling. With new long-term data-records for ATSR (17 years), UV-AI (35-years) and most recently IASI (10 years) it is also appeared tempting not only to capture anomalies but also to explore long-term temporal trends. As trends only address a relative change, high absolute accuracy may not necessarily be needed, as long as biases are consistent over time. It is known from other observations that global trends in AOD over the last 30 years are small, but general changes in some regions could be expected. It was however also demonstrated that for such data-records even on a regional basis reliable trend identifications proved to be difficult. The main reasons were inconsistencies between consecutive sensors (e.g. ATSR-2 vs AATSR), lack of retrieval detail and capabilities (e.g. poor AODc estimate with ATSR) and interpretation issues (e.g. altitude vs AAOD amount with UV-AI). Another way to support climate modeling (with Aerosolcci data products) is via general evaluations, via input in data assimilations and by constraining processes through relationships extracted from satellite retrievals at different spatial and temporal scales. Thus, one task applied different Aerosolcci data to improve aerosol component modeling, another demonstrated and compared the value of different Aerosolcci data in model assimilations and two studies focused on ‘observed’ retrieval relationships between retrieved Aerosolcci and associated cloud properties (retrieved with the same sensor). Constraining aerosol-cloud interactions (at different spatial and temporal) scales with ‘observations’ is extremely important for climate sensitivity and climate predictions, since the climate effect from added anthropogenic aerosol (the radiative effect at the top of the atmosphere at all-sky condition) is dominated by aerosol modifications to water clouds (the indirect effect) rather than by the added pure aerosol presence (direct effect). Those radiative forcing investigations with the ATSR data in a final activity however also demonstrated that the direct effect still dominates on solar absorption (impact on dynamics) and surface cooling (impact on surface processes).
3 TEMPORAL TRENDS IN AOD

SUMMARY
The ATSR record is potentially long enough (1995-2012) to explore long-term trends in AOD and its fine mode AODf and coarse mode AODc contributions. These AOD data were retrieved by three different retrievals (with support of ESA’s Aerosol_cci project). The concept is that, even if AOD retrievals differ and are absolutely inaccurate, several long-term data can reveal temporal trends, as long as retrieval biases are close to constant over time and results are consistent between different datasets. The ATSR record, however, is based on two similar but different sensors. While both sensors are relative stable over time, discontinuities in retrieved AOD during the overlap period exist with respect to coverage. This makes a consistent and inter-calibrated combination of ATSR-2 and AATSR a challenge. Thus, for a trend analysis using only the AATSR sensor data from 2003 to 2011 is a conservative choice with respect to sensor stability. In this period after 2003, on a global annual average basis no significant trend for AOD and AODf is detected by any of the three ATSR retrievals. However, all three retrievals indicate a shift in AOD and AODf away from Europe and the US to eastern and southern Asia in agreement with other satellite sensors, ground-based observations and our understanding of anthropogenic emission shifts. Still, these AODf shifts are weaker than suggested by global modeling. A derivation of trends for AOD with the complete ATSR-2 / AATSR time record, however, is challenging as retrievals over deserts are poor or missing. The strong dust AOD increases over Arabia as well as the dust AOD decreases over the Western Sahara, as retrieved by other satellite sensors (e.g. SeaWiFS, MODIS) are no clear features of the ATSR data record.

ANALYSIS
ATSR sensor data offer retrievals for the aerosol optical depth (AOD) at 550nm, as well as for the aerosol optical depth associated with the sub-micron size particles (AODf). Thus, by difference also the aerosol optical depth for super-micron size particles (AODc) is given. Aerosol optical depth data of the ATSR retrieval are provided with global coverage for more than 16 consecutive complete years (1996-2011). Since mid-visible AOD retrievals from the earlier ATSR-2 sensor (1995-2003) and the more recent AATSR sensor (2002-2012) agree quite well for the overlapping time-period (at least for the Univ. of Swansea retrieval), it is tempting also to look at temporal change. Even if there are regional retrieval AOD biases, changes over time can be interpreted as trends, as long as regional biases are consistent over time. For such a trend analysis, regions move in the focus, where AOD changes during the ATSR data record are expected. This includes changes due to general differences in the meteorology (e.g. dryer or wetter: mainly affecting concentrations of larger mineral dust aerosol) or due to increases or decreases in anthropogenic emissions (mainly affecting concentrations of smaller aerosol). Expectations are that over the last two decades, dryer conditions over Saudi Arabia yielded strong enhancements to (mineral dust) AODc while changed dynamics reduced the (dust) AODc outflow from northern Africa out over the Atlantic. For AODf anthropogenic emission data inventories suggest reductions to AODf over the US and Europe and strong increases to AODf over southern Asia and also over eastern Asia during the first half of the ATSR data record.
Figure 3.1 temporal changes in annual AOD for selected regions (left) by the ATSR SU retrieval

In the analysis of the Swansea ATSR (SU 4.21) AOD retrievals the temporal changes in annual average between 1996 and 2010 were investigated (year 2011 was discarded due to apparent calibration issues). Temporal changes of annual (total) retrieved AOD for selected regions (by color) are presented in Figure 3.1.

The regional AOD values roughly confirm expectations, with larger averages in regions of northern Africa, East Asia and Southern Asia. Jumps in the time series, in particular between 2002 (ATSR-2) and 2003 (AATSR) may be an artifact since regional coverage and sampling of the newer AATSR sensor were higher. Thus for a trend analysis it seems more robust focusing wherever possible on the more recent AATSR period (2003-2010). In this preliminary analysis a trend is discussed only if the long-term changes are large compared to the (inter-annual) variability.

For northern Africa (where average AOD values are largest) no clear trend is detectable, also as inter-annual variability is high. An increase in total AOD is revealed for southern Asia but only weakly for eastern Asia. There is only a weak AOD decrease over Europe and since 2002 possibly also over northern America. AOD data over Indonesia display considerable inter-annual variability and the unusually strong biomass burning in 1997 (at the beginning of the record) may falsely suggest a general negative trend. Similarly, when considering trends for southern Africa and America, the more intense biomass burning in the late 90ies especially over South America results in an apparent negative trend. Due to strong inter-annual variability in biomass burning regions a trend-detection in those regions will be difficult.

The AOD separation into fine-mode (AODf) and coarse-mode (AODc) helps to identify, if temporal change in AOD can be attributed to anthropogenic sources (e.g. pollution, roughly represented by AODf) or natural sources (e.g. dust, represented by AODc). AOD component trends are presented in Figure 3.2.

Figure 3.2 regional AODc and AODf (550nm) temporal changes for ATSR annual averages.

The identification of component trends over the entire ATSR data record is handicapped by apparent 'jumps' between 2002 and 2003 with the switch from ATSR-2 sensor data to AATSR sensor data. Still, the total AOD increase over southern Asia has apparent contributions from both AODc (natural aerosol) and AODf (anthropogenic sources). For eastern Asia the AOD components are relatively stable for the two sensor periods although the AODf seems slightly higher for the AATSR period. AODf trends and AOD decreases are correlated for Europe and northern America.

In the trend analysis absolute retrieval accuracy is not necessarily a requirement but side by side comparisons to bottom-up hindcast simulations (with ECHAM) nonetheless reveal ATSR (Univ.
Swansea) retrieval biases. Thus, the time-series for ATSR AODc and AODf are directly compared to nudged hindcast simulations with ECHAM in Figures 3.3 and 3.4.

As compared to the ECHAM model the ATSR retrieval shows higher AODc and AODf for northern Africa and lower values of AODf for Europe. Cloud contamination in ATSR at low AOD is indicated by relatively high minimum AODc values. Another difference appears in that many regional trends in modeling (e.g. AODf decrease over Europe or AODf increase over eastern Asia) are much stronger in global modeling compared to ATSR ‘observations’.

AOD trends can be also observed by complementary ground-based monitoring. While representative spatial sampling is limited, data quality of direct solar attenuation data is much higher than can be expected from satellite sensor data retrievals. Unfortunately, long-term monitoring sites (e.g. of AERONET) exist only over land and only in considerable density over Europe and northern America. AOD trends at individual AERONET sites for sufficiently long data records (within the 2000 to 2012 period) are presented in Figure 3.5.
The data confirm a general tendency for decreasing AOD trends over Europe and northern America. About half of the sites have a decreasing trend, half no trends at all. The corresponding ATSR satellite AOD trends are documented at AERONET sites via the web interface [http://aerocom.met.no/trends/](http://aerocom.met.no/trends/).

To further examine if these trends, which are likely associated with dominant fine-mode AOD in those regions, were actually detected by all the three ATSR retrievals (SU v4.3, ADV v2.30-plume, ORAC v4.01) time-series of AODf seasonal averages are presented for Europe, north America and southern Asia in Figure 3.6. Hereby time-series are presented separately for data associated with the ATSR-2 sensor (1995-2003) and the AATSR sensor (2002-2012). The agreement of retrievals from the two different sensors in the overlap period is only acceptable for Europe and northern America. And for those regions ATSR retrievals agree on AODf decreases over time, especially for Europe. For southern Asia the strong inconsistency in the overlap period requires to look at sensor data individually. For both ATSR-2 and AATSR periods by themselves strong AODf increases over time are indicated (as expected for increased emissions in that region).

For better sensor consistency AOD and AODf values of each ATSR retrieval are individually adjusted (as outlined in the Appendix) so that the entire ATSR data record can be applied in a more consistent way. Then for trend estimates changes the four-year average around 2010 (2008-2011) is compared to four-year average in the late 90ies (1996-1999). Based on the differences of these multi-year averages, the different ATSR retrievals consistently suggest for global averages small increases to AODf between 0.02 and 0.06 and slightly smaller increases to the total AOD. As a consequence, AODc experienced a weak reduction. Note that this general assessment approach is different from the more detailed regional examination on trends in chapter 9.
Another aspect, (nicely presented in Figure 3.6) is that the regular seasonal variations are much larger than any observed changes in long term AODf averages. This illustrates how difficult trend detection is even on a regional basis, even more so globally.
Figure 3.6 regional AODf (550nm) monthly changes of 3 different ATSR retrievals separated by associated satellite sensor: ATSR-2 1995-2002 (dashed), AATSR 2003-2012 (solid) for Europe (upper panel), North America (center panel) and Southern Asia (lower panel). Note that land only regions, other from figure 3.1 are used. See for the definition of the regions chapter 9.

The time-series of global annual averages of retrieved AOD by the three ATSR retrievals from 1996 to 2011 do not display a significant trend. As these retrievals do not consider that AODf over the last decade has become more absorbing (e.g. less sulfate, more BC), no trend could actually mean that AODf and AOD is slightly increasing.

Major results of the trend analysis are

- inconsistencies between ATSR-2 and AATSR sensor regional averages during the overlap period suggest that the most robust trend analysis should be limited to the relatively short AATSR sensor period (2003-2011)

- attempts to involve the entire ATSR data record (1996-2011) require adjustments based on retrieval comparison near the sensor transition time (2000-2004).

- one adjustment method applied to 3 different retrievals suggests for global averages a weak positive increase for AODf (0.01 to 0.06) and an increasing tendency for the total AOD (-0.02 to 0.06)

- regional shifts in AODf from Europe and northern America to southern and eastern Asia are detected. These shifts are consistent with known regional changes in anthropogenic emissions, but shifts are smaller than suggested by global modeling

- ATSR capabilities on AODc retrievals are limited. Retrievals over bright surfaces are poor or not successful (larger events may be missed) and AODc estimates are derived from differences between AOD retrievals and associated AODf estimates (higher uncertainty). Thus, the derivation of meaningful trends for AODc will be difficult.

- Investigations on AODf anomalies are encouraged, as ATSR is highly sensitive to pollution and wildfire which are major contributors to AODf variability.

- AODf anomalies indicate that AODf variability has decreased, in part since wildfire seasons (especially over S. America) of recent years are less intense than in the 90ies.
4 AEROSOL DIRECT RADIATIVE FORCING

SUMMARY

Retrieved AOD values from ATSR satellite sensor data from retrievals over almost 17 years are applied in an off-line radiative transfer code to yield the associated direct aerosol radiative effects at the top of the atmosphere (TOA) and at the surface. The simulations display strong regional and seasonal variability even from year to year, although global averages have only a small inter-annual variability. At the TOA larger net flux (defined as downward – upward flux) gains (climate warming) over dust source regions are more than balanced by net flux losses (climate cooling) over oceans. Regional variability is often linked to smaller aerosol (from wildfire and pollution) and these changes are better identified by reductions of net fluxes at the surface. Anthropogenic aerosol accounts for only 30% of today’s AOD and yields a similar small fraction for the global average TOA cooling (total: -0.9 W/m²; anthropogenic: -0.2 W/m²), although forcing patterns are quite different. For anthropogenic aerosol, clouds through their indirect effect are expected to add to today’s anthropogenic aerosol clear-sky cooling of -0.6 W/m² for overall cooling due to today’s anthropogenic aerosol near -1.0 W/m².

CONCEPT

Aerosol properties of satellite data are generally limited to estimates for the aerosol column amount, usually expressed by the aerosol optical depth (at a mid-visible wavelength). However, to address aerosol associated radiative impacts, additional data are needed, such as (1) aerosol properties for absorption and aerosol size, (2) the aerosol vertical distribution, (3) the presence of clouds, (4) the radiative properties (e.g. albedo, emissivity) of the surface and (5) the available solar energy. For the missing AOD data and data on aerosol size and absorption, values of the MAC aerosol climatology (Kinne et al., 2013) were substituted. The MAC aerosol climatology merges multi-annual monthly statistics from accurate ground based monitoring with monthly averages of spatial context from global modeling. Annual averages for mid-visible aerosol column properties for amount (AOD), absorption (AAOD) and size (FMF, Angstrom) of the MAC aerosol climatology are presented in Figure 4.1.

Figure 4.1 Annual average global distributions of the MAC aerosol climatology for amount (AOD, upper left), absorption (AAOD multiplied by 10, lower left) and size (AOD fine-mode fraction FMF,
upper right; Ångström exponent divided by 2, lower right). Values below the labels indicate global averages (large values) as well as northern (upper) and southern (lower) hemispheric averages.

From these mid-visible aerosol column properties wavelength dependent single scattering properties (AOD, SSA, ASY) are derived, which are needed to simulate aerosol direct radiative effects. The AOD vertical distribution is adopted from global modeling, tropospheric clouds are prescribed by the ISCCP cloud climatology and surface properties (i.e. solar albedo and temperature) rely global data-set derived from satellite observation or adapted by global modeling – as described in Kinne et.al, 2013. The uniqueness of applying the ATSR AOD retrievals over the MAC climatology is that inter-annual variability, unusual regional event and even long-term trends are revealed.

ATSR AOD

The ATSR AOD retrievals cover 16 complete from 1996 to 2011. Global annual average maps for the mid-visible AOD, retrieved with the Swansea University algorithm are presented in Figure 4.2.

![Figure 4.2 Annual average global distributions of AOD at 550nm for 16 consecutive years with the Swansea algorithm based on ATSR-2 sensor data for 1996 to 2002 and AATSR sensor data for 2003-2011. Values below the labels indicate global annual averages. White regions have no or not sufficient data coverage.](image)

The global annual averages for AOD did not significantly change over the 16 year data record. However there are regional variations, such as the strength in seasonal biomass burning over South America or maxima associated with unusual wildfire events, as in 1997 over Indonesia or in 2003 over Siberia. Also it should be noted that the ATSR AOD is larger than that of the MAC aerosol climatology so that the aerosol direct radiative effects are slightly stronger than that of the MAC climatology as illustrated in Figures 4.3 and 4.4 (the MAC climatology data are displayed in the upper left panels).

Figure 4.3 presents direct radiative effects for all (natural and anthropogenic) aerosols at the top of the atmosphere (TOA). Aerosols - in a climate context - both cool and warm, depending on the region and the aerosol type. Over brighter land surfaces the absorption by tropospheric aerosol is often sufficiently large to cause a surface reflectance dimming, thus warming, as over northern Africa. And not only soot (BC) but also mineral dust is absorbing. Admittedly dust absorption is weak but loading is often large. Also mineral dust aerosol sizes, especially near sources, are often so large, that
Elevated dust layers contribute to warming with a greenhouse effect. Over (relatively dark) oceans cooling dominates, as mainly (non-absorbing) sea-salt aerosol scatters solar energy back to space.

**Figure 4.3** Global annual maps for the aerosol direct radiative effects at the top of the atmosphere (TOA) and at all-sky conditions (with tropospheric clouds) for the 16 ATSR years (96…11). Also shown (in the upper left) are the radiative effects of the MAC climatology (MAC) and of a 4 year
average (8-11). Values below labels indicate global annual averages of locations where AOD values were retrieved. Note the year to year variability in annual patterns.

Figure 4.4 global annual maps for the aerosol direct radiative effects at the surface and at all-sky conditions (with tropospheric clouds) for the 16 ATSR years (96 … 11). Also shown (in the upper left)
are the radiative effects of the MAC climatology (MAC) and of a 4 year average (8-11). Values below labels indicate global annual averages of locations where AOD values were retrieved.

Considering the large differences in regional responses (in sign and amount), it does not seem right to condense to impact to a single value. However if we do so anyway, then the global average (as shown by averages in Figure 4.3) is slightly negative at -0.8 W/m² to cause an overall climate cooling. Thus, the aerosol direct radiative effect at TOA (at all-sky conditions) is a cooling.

Figure 4.4 presents aerosol associated radiation losses at the surface mainly by solar absorption and solar scattering back to space. These solar losses reflect the distribution of the AOD above clouds except for regions with elevated larger dust particles (e.g. over the Sahara and Arabia), where infrared re-radiation to the surface partially offsets the solar radiation losses.

An interesting aspect by applying time-varying AOD data from satellite remote sensing are changes in time for aerosol direct effects (at TOA and surface) at selected regions. For instance, at the surface the direct radiative effects over biomass burning regions display strong inter-annual variations (e.g. particularly strong in the late 90ies over South America) or the direct radiative effects reveal temporal trends (much stronger effects towards the end of the climate data-set [2008-2011] compare to the start of climate data-set [1996-1999]). These trends are not or less detectable for aerosol direct effects at the TOA, since the stronger varying aerosol types (or wildfire or pollution) have due to their significant solar absorption an almost neutral behavior with respect to net-radiation at the TOA.

Aside from the inter-annual variations, the direct aerosol effects also have a strong seasonality. For impacts at TOA and surface, seasonal radiative effects with ATSR AOD data (using 2008-2011 period AOD averages) are displayed in Figure 4.5 for both all-sky (with clouds) conditions and clear-sky (cloud removed) conditions.

![Figure 4.5 global seasonal maps for the aerosol direct radiative effects with ATSR 2008-2011 AOD data at TOA (top row) and surface (bottom) row at all-sky (left) and at clear-sky (right) conditions.](image-url)
The seasonal data indicate that radiative effects over the Sahara by dust are much stronger during (boreal) spring and summer and that the stronger pollution in the northern hemisphere during boreal summer is only indicated by reductions to the solar insolation at the surface (and not at the TOA). Another aspect is the comparison between all-sky and clear-sky aerosol direct radiative effects. With clouds the radiative effects are less negative as the clouds are allowed to mask the aerosol effect, as for instance over the oceans. At the TOA, lower altitude clouds in addition will offer a bright lower boundary that is dimmed by (absorbing) elevated aerosol for local TOA warming. Thus, on average the relative reductions to the negative direct aerosol forcing are stronger at TOA than at the surface.

In discussions of climate change the impact of just anthropogenic aerosol is of interest. Model simulations with best estimates for aerosol and precursor gas emissions for today and pre-industrial conditions reveal that anthropogenic aerosol accounts for only about 30% of today's AOD yet more than 50% in aerosol number concentrations, as mainly smaller aerosol sizes are added (directly or by condensation). Applying the fine-mode AOD fraction and the fraction of the fine-mode AOD that is identified as anthropogenic by global modeling, the ATSR AOD associated anthropogenic aerosol direct impacts were determined and are displayed for all-sky and clear-sky conditions in Figure 4.6.

![Figure 4.6 global seasonal maps for anthropogenic aerosol direct TOA forcing with ATSR 2008-2011 data at all-sky conditions (left) and at clear-sky conditions (right). Values below the labels indicate seasonal global averages.](image)

The comparisons between all-sky and clear-sky TOA radiative effects demonstrate the moderating effects of clouds with a push to less negative values. With clouds in many regions the TOA cooling is not only reduced but also reversed into a warming (e.g. over stratocumulus regions over the SE Atlantic during boreal summer and fall). In effect clouds reduce the global average cooling by direct anthropogenic aerosol from ca -0.6 W/m² to -0.2 W/m². However, there is also an indirect aerosol effect, as increased aerosol concentrations offers extra nuclei for cloud water to condense on - with impacts to cloud microphysics (e.g. smaller droplets) and even structure (e.g. cloud cover). Cloud microphysical effects alone (resulting in increased solar reflection by low altitude clouds to space) are expected to contribute with an additional TOA cooling on the order of -0.5 to -1.0 W/m². This more than offsets the clear-sky to all-sky cooling reductions for the direct effect of anthropogenic aerosol.

Thus, today's anthropogenic cooling by aerosol in total (direct and indirect effects combined) only masks on a global average only 30% of the warming by anthropogenic greenhouse gases. Regionally and seasonally however contribution can be significantly larger as aerosol impacts have a strong regional and seasonal character.

Major results of the aerosol direct radiative forcing studies are

- the ATSR AOD climate data record (1996-2011) reveals aspects on regional variability
- direct aerosol radiative effects have a strong regional and seasonal character
  - TOA flux: large increases over deserts, losses (-) over oceans: -0.9 W/m²
  - surface flux: losses in regions with larger AOD / smaller sizes: -4.5 W/m²
  - energy loss is larger at clear-skies: TOA: -2.2 W/m² / surface: -5.4 W/m²
- to put it into perspective, bottom-up global modeling (via emission data) tells us that today’s anthropogenic aerosol mainly contributes via the fine-mode AOD. In terms of total AOD today’s anthropogenic aerosol has only raised the total AOD by 30% but the aerosol number on average has increased by 50% (→ big potential to modify clouds)
- based on the from modeling predicted fine-mode anthropogenic AOD contribution:
  - anthropogenic direct TOA net flux loss: -0.2 W/m² (all) / -0.6 W/m² (clear)
  - anthropogenic indirect TOA effects are larger and uncertain: -0.5 to -1.0 W/m²
- clouds affect clear-sky TOA net flux loss by anthropogenic aerosol in different ways
  - cloud over aerosol (aerosol effects are reduced) → smaller losses
  - aerosol above clouds (brighter background for aerosols) → smaller losses
  - brighter clouds (as more aerosol reduce drop size) → larger losses
  - overall clouds are likely to increase clear-sky forcing (from -0.6 to ca -1.0 W/m²)

REFERENCES

5 AEROSOL-CLOUD INTERACTIONS

SUMMARY

This user study investigates links between satellite retrieved aerosol and cloud properties. A main focus is on links between retrieved cloud liquid water path (LWP) and aerosol index (AI, as proxy for aerosol concentration). This relationship seems complicated as different outcomes are possible. In theory smaller droplets expected from enhanced aerosol concentrations can (1) extend cloud lifetime (positive feedback, as precipitation is delayed or suppressed) but alternately (2) reduce cloud-lifetime (negative feedback by faster evaporation during entrainment mixing with dry air). Global modeling and the analysis of associated satellite retrievals (even by different sensors) show that the covariation of relative humidity masks the relationship of liquid water path relationship to aerosol number. After applying methods to reduce the impact of relative humidity clear relationships for specific atmospheric conditions are revealed to advance process understanding and constrain process parameterizations.

AEROSOL CLOUD INTERACTIONS

The AATSR sensor retrievals do not just offer estimates for aerosol optical properties. Also cloud properties can be retrieved from AATSR data. However, reliable cloud (microphysical) retrievals require overcast conditions, whereas aerosol retrievals require cloud-free conditions. Thus, a single satellite sensor cannot provide aerosol retrievals and cloud retrievals at the same time and location. Still, spatial associations (statistics) on larger scales (e.g. for a 100x100km² region, a typical resolution in global modeling) allow insights into aerosol-cloud relationships. Such relationships offer useful constrains to (process) representations in global modeling, whose understanding is often derived from interactions and observations at much smaller scales (e.g. cloud brightening by ship exhaust).

The impact of aerosol on water clouds is better understood and less dependent on aerosol type as the impact on mixed-phase or ice clouds. For water clouds enhanced aerosol concentrations lead to a smaller cloud droplet size (more nuclei are available for water to condense on) as long as the cloud water content remains the same. A smaller droplet size will delay the onset of precipitation (to extend cloud lifetime) but smaller sizes will also evaporate faster when mixing with dryer air (to reduce cloud lifetime). As a result both the cloud albedo as well as the cloud cover may change. From these aerosol-cloud interactions (ACI) both the intrinsic (cloud albedo change while liquid water path is allowed to change) and the extrinsic (cloud cover change) effective radiative forcing due to ACI (ERF_{aci}) can be estimated. The ACI are examined in more detail also with respect to cloud type and environmental conditions below.

To represent aerosol number concentrations, commonly the product of two retrieved aerosol column optical properties is picked: the product of aerosol optical depth (AOD) and Ångström exponent. This aerosol index (AI) emphasizes the presence of smaller aerosol sizes, which control the number concentrations. For aerosol cloud process understanding most interesting are relationships that address responses to cloud microphysics (e.g. effective radius, liquid water content or droplet number concentration). Hereby these relationships are explored as a function of their environment (e.g. aerosol number, relative humidity, atmospheric stability, precipitation state).

To compute the statistical relationships at larger scales we use a new Cloud-Aerosol Pairing Algorithm (CAPA; Christensen et al., 2017) together with the AATSR-ORAC retrieval. 1 km cloud pixels are paired with the nearest 1km aerosol pixel (linearly interpolated from 10 km aerosol products) between 15 and 150 km in the e.g. 100x100km² area. This new approach has several advantages: (1) increased number of aerosol-cloud pairs to compute the statistical relationships, (2) reduced contamination by scattering of sunlight at the sides of clouds that illuminates the aerosol field (e.g. by undetected clouds in assumed cloud free areas or by swelling of aerosol particles in the humid air surrounding clouds) and (3) reduced effects of numerical aggregation. To further minimize the effect of aggregation, for larger areas (regional/global scale) a weighted mean (weighted by the number of aerosol-cloud pairs) is computed from statistical relationships (e.g. 100x100km²).

As can be seen in Figure 5.1 for (four) stratocumulus cloud regions, the AOD and the aerosol particle size (Ångström exponent decreases) increase the closer the nearest cloud is for MODIS and the AATSR-ORAC retrieval. The contamination is strongly reduced for distances larger 15 km, as done in the analysis by Christensen et al. (2017).
Figure 5.1 AOD and Ångström exponent as a function of the distance to the nearest cloud retrieval for JJA 2008 for AATSR (black) and MODIS collection 6 (red). The number of AATSR pixels for each 1-km width bin (green) is also shown (Christensen et al. 2017 ACP).

Excluding aerosol retrievals near clouds has an impact on statistical aerosol-cloud relationships and the derived ERF\textsubscript{aci}. Figure 5.2 shows that the intrinsic ERF\textsubscript{aci} as well as the extrinsic ERF\textsubscript{aci} are substantially decreased when near cloud aerosol retrievals are excluded. The reduction is similar for AATSR and MODIS retrieval products. Figure 5.2 further shows that the removal of aerosol retrievals for near clouds in L2 products (green vs blue) also yields more accurate L3 products (yellow vs red).

Figure 5.2 ERF\textsubscript{aci} for AATSR-ORAC and MODIS-ORAC L2 and L3 products with and without excluding aerosol 15km near clouds, a) intrinsic (cloud albedo) ERF\textsubscript{aci}, b) extrinsic (cloud cover) ERF\textsubscript{aci} (Christensen et al. 2017 ACP).
For AATSR and MODIS retrievals the effect of humidity on AOD and AI are reduced by CAPA processing. As the global model data of ECHAM6-HAM2 is only available at a much larger horizontal resolution of 1.875°x1.875° a similar approach as for the satellite data is not possible. Instead one can remove the aerosol water in a model in the computation of AOD and AI (→ AI-dry). In Figure 5.3 the decrease in the susceptibility of LWP to AI (Figure 5.3a) and of LWP to AI-dry (Figure 5.3b) are shown. As these susceptibilities are affected by wet scavenging, Figures 5.3c and 5.3d show only non-raining scenes for LWP susceptibility to AI-dry. The negative susceptibilities in Figures 5.3c and 5.3d are caused by convective moderate and heavy precipitation. Removing the effect of aerosol swelling by removing aerosol water decreases the strength of the LWP/AI-dry relationship (Figure 5.4).

In Figure 5.4 are changes of the cloud liquid water path (LWP) examined as a function of aerosol index (AI) - with further stratifications into specific atmospheric states. These susceptibilities [dln(LWP)/dln(AI)] based on AATSR retrievals with the ORAC-CAPA algorithms are presented in Figure 5.4 along with comparisons to those using MODIS-CERES data and to those diagnosed in the ECHAM6-HAM2 global aerosol-climate model.
Figure 5.4 Susceptibilities of cloud liquid water path (cloud top pressure > 500 hPa, cloud top temperature > 273.15 K) to aerosol number concentration (approximated by the aerosol index AI = AOD × Ångström). Values for ln(LWP)/ln(AI) are compared for different environmental regimes based on model results (ECHAM6-HAM2, green, ECHAM6-HAM2 with AI-dry, violet), on satellite retrievals by AATSR-CAPA (red) and MODIS-CERES (blue). The left panel displays non-raining scenes and the right panel displays raining scenes (Neubauer et al. 2017 ACP).

For LWP versus AI all eight atmospheric permutations involving, precipitation (non-rain: $R_{\text{eff}} < 14 \, \mu m$, rain: $R_{\text{eff}} > 14 \, \mu m$), stability (unstable: LTS < 17K, stable: LTS > 17K) and moisture in the free troposphere (dry: RH$_{\text{FT}}$ < 40%, moist: RH$_{\text{FT}}$ > 40%) tendencies are examined. AATSR-CAPA data suggest positive LWP/AI relationships for non-raining conditions but weak LWP/AI relationships of both signs for raining conditions. In contrast, MODIS-CERES retrievals display for all non-raining conditions negative LWP/AI relationships but for positive LWP/AI relationships for raining. In global modeling (with ECHAM6-HAM2) relationships LWP/AI relationships for all tested environmental are positive and much stronger. The negative LWP/AI relationships in the MODIS-CERES data at non-raining conditions have been interpreted as the effect of mixing of dry air from the free troposphere in the boundary layer (cloud top entrainment). That this is not observed in the AATSR-CAPA relationships could be due to differences in sampling between AATSR and MODIS or the cloud retrieval of AATSR-CAPA or MODIS-CERES or how rain is diagnosed for the AATSR-CAPA data via cloud top effective radius. In contrast, the aerosol retrievals over ocean agree well between AATSR-CAPA and MODIS-CERES.

Even though observational tendencies for the same environmental class do not always agree in sign, their feedback strength is significantly smaller than diagnosed in global modelling. Possible explanations for overestimates in global modelling are (1) missing entrainment (mixing processes with drier air), (2) overestimates of cloud lifetime effects (due to insufficient buffering mechanisms), (3) the use of a diagnostic precipitation scheme and (4) co-variation of humidity.

Simulations with a sophisticated prognostic precipitation scheme in ECHAM6-HAM2 show that while the ratio (auto-conversion / (accretion + auto-conversion) decreases, the LWP/AI relationship intensifies in stratuscumulus regions compared to the diagnostic precipitation scheme. The common drizzle in stratuscumulus regions is captured with the sophisticated prognostic scheme leading to higher liquid water path in those regions compared to the diagnostic scheme where only rain is possible. Furthermore the prognostic scheme increase AI over the oceans and AOD in stratuscumulus regions while AI over land decreases and global mean AOD is decreased. The increase in AI, AOD and LWP and thereby the LWP/AI relationship with the sophisticated prognostic precipitations scheme shows how important it is essential first to represent clouds in a model properly before simulating aerosol-cloud interactions. It further shows that the larger susceptibilities in global models cannot be explained by the use of a diagnostic precipitation scheme.
The LWP/AI-dry relationship is in better agreement with observed relationships although the dependence of atmospheric state is weaker in the model. This indicates that the simulated cloud top entrainment or other buffering mechanisms are too weak or missing. Interestingly, in global modeling the positive LWP/AI relationships are strongest in areas of low cloud cover (as illustrated in Figure 5.3). As a weighted mean is used in the computation of the global averages (listed in Figure 5.4), these averages are not affected by the high values in regions with few aerosol-cloud data pairs. The potentially strong positive biases in global modeling raise the question, to what degree the spatial distribution patterns in Figure 5.3 can be trusted. Global annual averages for intrinsic (cloud micro-physics) and extrinsic (cloud lifetime) effective radiative forcing (ERF) are compared in Figure 5.5.

**Figure 5.5** ERF\textsubscript{aci} for ECHAM6-HAM2 with and without aerosol water and AATSR-CAPA and MODIS-CAPA/CERES L2 and L3 products with and without excluding aerosol 15km near clouds, a) intrinsic ERF\textsubscript{aci} b) extrinsic ERF\textsubscript{aci} (Neubauer et al. 2017 ACP).

The model derived relationship (including aerosol water; ECHAM6-HAM2 – all scenes) translates into a TOA intrinsic forcing near -3.03 W/m\textsuperscript{2}, whereas those linked to AATSR-CAPA-L2 and MODIS-CAPA-L2 yield just -0.49 W/m\textsuperscript{2} and -0.60 W/m\textsuperscript{2} respectively. The TOA intrinsic forcing computed for the model derived relationship excluding aerosol water (ECHAM6-HAM2 (dry) – all scenes) leads to a TOA intrinsic ERF\textsubscript{aci} (-0.80 W/m\textsuperscript{2}) closer to those of AATSR-CAPA-L2\_15km (-0.28 W/m\textsuperscript{2}) and MODIS-CAPA-L2\_15km (-0.24 W/m\textsuperscript{2}) excluding near cloud aerosol. The extrinsic ERF\textsubscript{aci} in global modeling is small when excluding aerosol water/near cloud aerosol and depends furthermore on the spatial scale of the analysis (Chen et al., 2014).

Major results of the aerosol-cloud interaction studies are

- liquid water path relationship to aerosol number \([\text{dln}(\text{LWP})/\text{dln}(\text{AI})]\) in modelling is affected by aerosol water uptake in humid environments around clouds
- the AATSR and MODIS associations an improved cloud aerosol pairing algorithm (CAPA, Christensen et al., 2017) minimizes this water uptake biases and reduces effects by cloud contamination, aggregation or 3D effects
- the (diagnosed) removal of aerosol water in global modelling resulted in a weaker liquid water path relationship to aerosol number \([\text{dln}(\text{LWP})/\text{dln}(\text{AIdry})]\) (more like satellite observations)
- AATSR data suggest no cloud top entrainment for non-raining scenes (unlike MODIS – possibly related to how precipitation is diagnosed or differences in sampling)
REFERENCES


6 LONG-TERM DATA RECORD ON UV AEROSOL INDEX

SUMMARY
The ultraviolet (UV) aerosol index (AI) provides qualitative information on elevated aerosol absorption. Combining data from different sensors a stable record since 1978 has been developed. Assuming that aerosol altitude and also aerosol absorption strength do not change significantly on a regional and seasonal basis interannual variability for regional wild-fire (and dust) seasons strength is revealed. In the context of strong interannual variability the data-set, however, is too short to identify significant regional trends in absorption of elevated aerosol.

UV Aerosol Index - 35+ years
The UV absorbing index is based on satellite remote sensing data at two UV wavelengths (near 340 and 380 nm). While the main purpose for remote sensing at these wavelengths is the retrieval of the atmospheric ozone content, it turned out that these sensor data also provide information on absorption of elevated aerosol, as absorbing such aerosols (mainly mineral dust and carbonaceous aerosol from wildfires) dim the molecular (Rayleigh) scattering of the atmospheric background below the aerosol. The higher the absorbing, the stronger the Rayleigh background and the larger the Rayleigh losses. The UV aerosol index (UV Al) quantifies these Rayleigh losses (1-weak, 5-strong). Thus any quantification of aerosol absorption requires that the aerosol altitude is known. As the aerosol altitude information is not available from these ozone satellite sensors, the UV-Al information is only qualitative but it still could be quite useful to capture variability. However, if aerosol altitude is provided (e.g. by global modeling or even better by active remote sensing via a space-lidar) then quantitative estimates for aerosol absorption are possible - although only for absorption in the UV (which often differs from the mid-visible absorption, where aerosol-radiation interaction is strongest).

Assuming that on a regional and seasonal basis the aerosol altitude and also the absorption potential (e.g. the co-single scattering albedo) did not change significantly over time, then with continued retrievals, temporal variations in aerosol source strength can be explored. Thus, with Aerosol_cci support a continuous a data record since 1978 (thus almost than 40 years) was assembled based on different satellite sensors as illustrated in Figure 6.1,

![Figure 6.1 satellite sensors that contributing to the ongoing UV-Al data-record since 1978. In the last 10 different satellite sensors contributed to the years UV-Al data record](image)

This longterm UV-Al data record is now applied to two major wildfire regions. One region is central western Africa, where the biomass burning season occurs from Jul to Oct and the other region is southern central America, where the biomass burning season occurs from Aug to Oct. These UV-Al regional monthly time-series are compared to simulations by two global models (GOCART and TM5) in Figure 6.2 for central western Africa and in Figure 6.3 for southern central America.
Figure 6.2 Temporal variations for the satellite data-based UV-AI index for southern central Africa (top panel) and complementary simulations for the UV aerosol absorption (AAOD, 350nm) by the GOCART model (center panel) and for the mid-visible aerosol absorption (AAOD, 550nm) by the TM5 model (lower panel) based on processed emission data assumptions.

The UV-AI data over central western Africa demonstrate the seasonality for elevated absorbing aerosol - associated with wildfire burning maxima in boreal summer and fall. While the minima are relative stable, maxima slightly vary from year to year. It remains however unclear, if larger seasonal UV-AI maxima are related to a higher aerosol elevation or due to more intense wildfires. The model simulations with the GOCART model and the TM5 model address in their seasonality the total aerosol absorption. The GOCART simulations are more useful as they address absorption in the same spectral region of the UV-AI retrieval, although there are uncertainties with assumed emissions and processing in the model. While in year-to-year variability there seems a weak correlation, the inter-annual maxima of the GOCART model output (for BC) display a much higher variability, as if during intense wildfire seasons the absorbing aerosol is on average at a lower elevation. The mid-visible aerosol absorption data of TM5 are higher than the UV aerosol absorption data of GOCART. This is inconsistent, but again these are different models with different processing chains.

The comparisons for the seasonal wildfire burning over central southern America are similar. The timing of the seasonal maxima is well captured and (again) inter-annual variations for aerosol absorption maxima are stronger in the models then for the UV-AI of the satellite data. Interestingly, both models do not reproduce the seasonality which is quite apparent from the ATSR climate data record (see Figure 4.4) so that the given model reference (as there are potential simplification with the emission data input) has to be viewed with caution.

Finally, in the context of the long data-record, attempts were made to explore UV-AI trends as attempted in Figure 6.4 for western Africa (wildfire maxima from Nov to Feb) and central western Africa (wildfire maxima from Jul to Oct).
Figure 6.3  Temporal variations for the satellite data-based UV-AI index for southern central America (top panel) and complementary simulations for the UV aerosol absorption (AAOD,350nm) by the GOCART model (center panel) and for the mid-visible aerosol absorption (AAOD,550nm) by the TM5 model (lower panel) based on processed emission data assumptions.

Figure 6.4  Temporal long-term trends of the satellite data-based UV-AI index data for southern central Africa (top panel, labeled ‘WestAfrica’) and for West Africa (lower panel, labeled ‘Sahel’). The green dashed line is a fit to the seasonal minima to demonstrate the stability of the time-series. The blue dashed line: is a fit to the seasonal maxima, indicating the trend in aerosol source strength (assuming similar absorption and altitude) over time. Different colors indicate datasets from different satellite sensors: TOMS (black), GOME-1 (red), SCIAMACHY (brown), OMI (green), GOME-2A/B (blue).
In the trend explorations of Figure 6.4 there are rather ‘optimistic’ trends, considering the different satellite sensors. Moreover, even such a trend would be significant (which is highly doubtful in the context of inter-annual variability and different sensors) then there is the question how to interpret such as trend (as a decreasing UV-AI trend could be caused by a lower altitude placement, a less absorbing aerosol type (e.g. lower BC fraction) or a lower aerosol amount).

Major results of the UV-AI long-term data record are

- The UV-AI long term data-record composed from different sensor data is relative stable
- The UV-AI provides qualitative information on elevated aerosol absorption
- Applications over central Africa and southern America regions with seasonal wildfire activity reproduce the seasonality of elevated aerosol absorption very well
- The interpretation of inter-annual variability and even trends in terms of wildfire intensity is limited
- The use of the UV-AI data records by the climate modeling community is not straightforward and requires a use of the observation operator (UV-AI simulator)
7 ASSIMILATION OF IASI DUST AOD

SUMMARY

A case study of the Barcelona computing center (BSC) aims to showcase the potential that infrared IASI retrievals have to improve the prediction (and along with it the monitoring) of mineral dust. With support via ESA’s aerosol CCI project four different retrieval approaches were applied to the same IASI sensor data. Assimilations with the different IASI data-sets are compared to forecast output (without assimilation) in evaluations against AERONET reference data. The DLR (or IMARS) retrieval disqualifies itself by a very poor correlation, the MAPIR retrieval yields way too strong dust AOD estimates, the LMD retrievals show a too noisy dust field. Thus, by default, ULB retrievals have the highest potential for data assimilation.

ASSIMILATIONS

The NMMB-MONARCH is coupled with an ensemble-based data assimilation technique known as LETKF (Pérez García-Pando et al., 2011; Di Tomaso et al., 2017). For this purpose the model is run in ensemble forecast mode, where the ensemble perturbations are based on known uncertainties in the physical parametrizations of the mineral dust emission scheme. Model equivalent of the observations are calculated mapping the ensemble mean state vector into the observation space through horizontal interpolation at observation location, and calculation of total extinction from the model mass concentration profile assuming dust spherical, non-soluble particles distributed in 8 model size bins.

Four different retrievals were applied to the same IASI sensor data and yielded different estimates for the distributions of (mid-visible, 550nm) dust AOD as illustrated in Figure 7.1

Figure 7.1 comparison of multi-annual (2008-2011) maps for coarse-mode dust AOD at 550um by four different IASI retrieval approaches (DLR(IMARS) v5.2, LMD v2.1, MAPIR v3.x, ULB v8.0).
Global assimilation experiments have been run with the NMMB-MONARCH chemical weather prediction system and four IASI dust datasets retrieved with the ULB v8, MARIR v3.5, IMARS v5.2 and LMD v2.1 algorithms. Gridded 1x1 degree level 3 AOD estimates at 550nm (spatially aggregated from level 2 data and associated uncertainties) are applied to avoid the assimilation of sub-grid features. Model output is generated every 6 hours at 0, 6, 12 and 18 UTC, where each sub-daily slice is based on the Level 2 retrievals contained in an interval of +/- 3 hours around those times. The assimilation results with the four IASI data-sets from March to June 2015 are compared in Figure 7.2

![Figure 7.2 NMMB-MONARCH v1.0 model results for March – June 2015 by assimilating Level 3 IASI dust AOD (550 nm) data of the ULB v8 (upper left), LMD v2.1 (upper right), MAPIR v3.5 (lower left) and IMARS v5.2 (lower right).](image)

The four IASI analyses (averaged over March-June 2015) display the largest differences closer to the source regions. The assimilation with MAPIR data yields the highest AOD values everywhere, while the LMD analysis stands out for higher AOD values at latitudes above 40 degree north.

Temporal averages of differences between analyses and a free run (an ensemble forecast run without data assimilation) are illustrated in Figure 7.3. Assimilation correction tendencies of individual IASI data-sets show some similarities. Near dust sources dust AOD values are forced to be lower than in the forecast model when assimilating the IMARS, LMD and ULB products. This applies mainly for North Africa but also to some degree for Arabia and East Asia. In contrast, in Central Asia and over more remote regions there is a push to higher dust AOD values. The LMD products stands out for producing differences compared to the reference experiment in a more extended area over the ocean compared to the other three products, while MAPIR produces almost everywhere higher values of AOD compared to the reference experiment.

An evaluation of the IASI data assimilation is performed by comparing model of dust AOD data (at 550nm) to measured AOD output at different AERONET sites. For AERONET AOD measurements dust-dominated conditions are identified using the approach of Basart et al. (2009) as follows: AOD is classified as “Dust” AOD when the associated AE < 0.75; we set “Dust” AOD to 0 when the associated AE > 1.3; we identify a mixed aerosol type when the associated 0.75 < AE < 1.3. The latter values are excluded from the validation. Time-series for March-June 2015 are compared in Figure 7.4 for one of the AERONET sites (IER_Cinzana). The assimilation output associated depends on the applied IASI datasets and dust AOD predictions differ strongly. The highest dust AOD
estimates involve the MAPIR retrieval application. At more meaningful larger AOD values (AOD >0.3) of AERONET the MAPIR data generally yields too high AOD values, while all other three data-sets (ULB, LMD and IMARS) yield too low AOD values.

A wider statistical evaluation by involving all AERONET sites with dust AOD contributions is offered in Figure 7.5, where root mean square error (RMSE), mean error (BIAS), standard deviation of the error (SD), fractional gross error (FRGE) and correlation coefficient (CORR) are compared.

**Figure 7.3** Differences between assimilation analyses and free runs by assimilating ULB v8 (upper left), LMD v2.1 (upper right), MAPIR v3.5 (lower left) and IMARS v5.2 (lower right).

**Figure 7.4** Comparison of assimilated dust AOD at 550nm from March to June 2015 to ground-monitoring at the IER_Cinzana (6W/13N) AERONET site in dust-dominated conditions.
Statistics of comparison to level 1.5 AOD data (at 550nm) of AERONET sites with significant contributions by dust for the standard forecast model (CONTROL) and assimilations (DA) with the four IASI data-sets. Compared are mean error (BIAS), root mean square error (RMSE), correlation coefficient (CORR), fractional gross error (FRGE) and fractional gross error (FRGE).

In Figure 7.5 only matches within a +/- 30 minute time window between cloud-screened (Level 1.5) AERONET data and site interpolated model output are considered. Overall all the assimilation experiments increase the bias towards AERONET compared to the reference experiment, with the exception of the MAPIR experiment, which produces some overestimation of AOD compared to AERONET. The assimilation of the IMARS product produces the lowest global scores in terms of RMSE and correlation coefficient, while the assimilation of LMD product is globally overall neutral. Slightly reduced RMSE and higher correlation coefficients than the Control experiment are reported globally for the MAPIR and ULB experiments. As IMARS disqualifies itself by a very poor correlation, and as MAPIR seems to yield too strong dust AOD estimates while LMD has a too noisy dust field, ULB seems the retrieval algorithm with the highest potential for data assimilation.

Still, retrievals are far from perfect (e.g. missing source strength) and assumption to size (which more advanced IASI retrievals should be able to extract) define spectral conversions which potentially could destroy a quality infrared AOD retrieval by deriving an inappropriate mid-visible AOD equivalent. For instance the better performing ULB algorithm assumes a fixed 2(VIS)/1(IR) ratio, which may apply for remote regions, where dust sizes are smaller, but certainly would not apply near dust sources where dust size are larger and where a 1(VIS)/1(IR) ratio would be expected. However using such a ratio near dust sources would degrade the ULB performance.

**IMPACT OF OBSERVATION UNCERTAINTY**

Three different characterizations of observation uncertainty have been compared for the assimilation of the ULB v8 retrievals: (i) a pixel by pixel uncertainty as estimated by the data provider, (ii) a pixel by pixel uncertainty according to a linear model (AOD$_{unc}$ = 0.1 + 0.54 * AOD), and (iii) a spatially and temporally constant value for the uncertainty (AOD$_{unc}$ = 0.35). Time-series for March-April 2015 are compared in Figure 7.6 at 4 AERONET sites, and show that the analyses produced with the different error characterizations differ between each other for some specific dust events. As expected, the characterization of the observation uncertainty has a relevant impact on the analysis estimation: under/over representing observation uncertainty might translate to giving a higher/lower weight to the observations with respect to the model first-guess.
**Figure 7.6** NMMB-MONARCH v1.0 model results from March to April 2015 in the reference experiment (Ensemble Free Run, blue), and by assimilating ULB v8 with a pixel by pixel characterization of the uncertainty as estimated by the data provider (DA ULB, red), or through a linear model (DA ULB linear, green), and with a constant value for the uncertainty (DA ULB constant, yellow) at the Dakar (top left), Banizoumbou (top right), IER_Cinzana (bottom left), and Ilorin (bottom right) AERONET sites in dust-dominated conditions.

Major results of the IASI data assimilation are

- ULB IASI retrievals yield strongest assimilation benefits over the forecast
- IASI retrievals tend to produce an analysis that underestimates dust AOD near source regions, with the exception of MAPIR retrievals which produce an overestimation of dust AOD everywhere
- further studies are needed to optimally characterize observation uncertainty for IASI data assimilation

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### 8 EVALUATION AND IMPROVEMENT OF THE CCM EMAC

**SUMMARY**

The aerosol module GMXE of the ECHAM5/MESSy (EMAC) global circulation model with chemistry was evaluated and improved with the help of Aerosol_cci retrieval products for troposphere and stratosphere. The simulations of seasonal patterns dust AOD now agree well for both, mid-visible and far-IR data. After the updates 2002 to 2012 simulations of aerosol extinctions in the lower stratosphere and upper troposphere agree well to GOMOS retrievals (at three different solar wavelengths).

**EMAC**

The EMAC model has been updated. It combines the ECHAM global circulation model with a recently improved GMXE modal aerosol module for aerosol components and the Modular Earth Submodel System (MESSy) for chemistry. For tropospheric aerosol properties emission data from MACCity and GFED are applied. EMAC is now evaluated also in comparisons to satellite retrieval products offered by ESA’s Aerosol_cci effort.

**EVALUATION (troposphere)**

A central element focused on the adjustments to the dust emission scheme and dust size distribution to match satellite retrieved AOD and simulated AOD patterns. Hereby dust AOD (ULB v8) IASI (based on a neural network learning) retrievals in the infrared (at a wavelength of 10 µm) served as benchmark (Klingmüller et al. 2017) for larger dust sizes. The global distributions for the 2011 annual average dust 10um AOD of the new EMAC model version (low top, high horizontal resolution, T106/L31, nudged) and IASI are compared in Figure 8.1

![Figure 8.1](image-url)  
*Figure 8.1: Annual mean 10 µm dust AOD for 2011 simulated by EMAC with revised dust emission scheme (upper panel) and the ULB.v8 retrieval for the IASI sensor (bottom panel).*
The comparison of the patterns of the annual averages is encouraging, although the Sahara maximum is lower and the maximum over the Taklamakan desert more or less missed, depending on resolution. The spatial correlation (of the annual averages) to IASI data is 0.91 (compared to 0.81 of the previous version).

Previous EMAC versions where tuned to AOD products for mid-visible wavelengths (MODIS, AERONET) but had never before been evaluated at 10µm, so that a large uncertainty of the dust particle size remained. Additionally tuning to the IASI retrievals at 10 µm considerably reduces this uncertainty, which is crucial for the dust effect on radiative transfer as well as the atmospheric residence time and transport of dust.

One of the crucial parameters affecting the size distribution in the EMAC model is the threshold radius between accumulation and coarse mode. Increasing this threshold radius results in a larger fraction of dust emitted into the accumulation mode and a less likely transfer of accumulation mode particles into the coarse mode. This adjusts the accumulation to coarse mode mass ratio and thus the 550 nm to 10 µm AOD ratio. Increasing the threshold radius from initially 0.5 µm to 1 µm proofed to yield more realistic results with the assumed dust-emissions in EMAC. In the process, further parametrization details had to be considered to avoid a spurious drift of the coarse mode to larger radii which we identified by comparing the Saharan dust outflow over the Atlantic with IASI observations in Figure 8.2.

**Figure 8.2**: Identification of an erroneous dust size assumption in EMAC. The model simulated dust AOD at 10 µm and the transport across Atlantic in July 2010 of the model (left) was much lower and weaker than those of Aerosol_cci retrievals with IASI_ULB.v7 for the same month (right). This model bias was fixed by reducing the assumed dust aerosol size in the EMAC model.

The modified dust scheme model yielded now not only better matches in maxima and transport to IASI in the infrared, as illustrated in Figure 8.1, but also in regions of dominant contributions to the mid-visible optical depth (at 550nm) to retrievals by MODIS and ATSR, as illustrated in Figure 8.3.

**Figure 8.3**: Annual mean AOD 550 nm (not just dust AOD) for 2011 simulated by EMAC (upper left) with its revised dust emission and size scheme in comparison to those of the MODIS retrieval (coll. 6, upper right) and two different ATSR retrievals (SU 4.3 lower left, ADV 2.31, lower right)
These efforts resulted in a model configuration which yields realistic results for the AOD both at visible wavelengths as illustrated in Figure 8.3 and in the infrared as illustrated in Figure 8.1. This model version contains a sophisticated scheme for secondary organic aerosol formation which is important in the regions with biomass burning.

EVALUATION (stratosphere)

The EMAC global model was then applied at T42/L90 resolution (2.8°, to 80km) to simulate with its modal size scheme (4 soluble and 3 insoluble size-modes, with a boundary between fine and coarse mode at 1.6µm diameter) the stratospheric and tropospheric aerosol extinction. Boundary conditions for organic and black carbon and dust scheme are as in the tropospheric configuration. The resulting global distributions for dust AOD (at both a mid-visible and far-IR wavelength) and for fine-mode AOD of that model version are compared in Figure 8.4.

Figure 8.4: Comparisons for annual maps for dust AOD in the far-IR (top), for dust AOD in the mid-visible (center) and for fine mode AOD (bottom) between Aerosol_cci retrieval products (left) and the EMAC model (right).
The comparisons between AOD maps from satellite retrievals and bottom-up modeling show similar patterns but not a perfect agreement. Both data-sets are results of model simulations with assumptions, with certainly more of those in bottom-up modeling. In modeling there is more (smaller particle) dust transport off continents and dust AOD values over central Asia (Pakistan, Taklamakan desert) might be too strong. When comparing to ATSR data though it has to be kept in mind that ATSR’s Swansea AOD retrieval overemphasizes dust AOD over continents (e.g. Sahara, Arabia, South America or Australia). There are also significant differences for the fine-mode AOD (from pollution and wildfires). The AOD associated with pollution is too strong over China and Europe but too weak over India, most likely related to the assumed emission data which include extrapolations. Also aerosol formation from wildfires sources (e.g. western Africa) appears to be too weak, pointing to the need for a more detailed modeling of secondary organic aerosol in this model version. The outflow to the Pacific from China appears to be too strong but this might be due to different meteorology in the simulation without nudging.

With this model version decadal stratospheric aerosol simulations were conducted. Volcanic SO$_2$ injections into the stratosphere are estimated from the MIPAS IR sensor and, in case of data gaps, from GOMOS extinctions (in total 230 events). Simulated aerosol stratospheric extinctions from 2002 to 2012 are compared in Figure 8.5 to 8.7 to retrieved GOMOS extinctions at 350nm, 550nm and 750nm.

Figure 8.5: comparison of stratospheric aerosol extinctions (in log10 scale) based on GOMOS retrievals (top) and EMAC model simulations (bottom) at 350nm wavelength
**Figure 8.6:** Comparison of stratospheric aerosol extinctions (in log10 scale) based on GOMOS retrievals (top) and EMAC model simulations (bottom) at 550nm wavelength.

**Figure 8.7:** Comparison of stratospheric aerosol extinctions (in log10 scale) based on GOMOS retrievals (top) and EMAC model simulations (bottom) at 750nm wavelength.
It looks like that the upward transport of Asian desert dust and organics with the Indian summer monsoon is important to explain the regional and seasonal extinction patterns in the lowermost stratosphere and upper troposphere as observed by GOMOS. The peaks near 18km are due to volcanic sulfate.

Major results of the EMAC simulations are:

- Simulated dust AOD distributions generally agree with the satellite data in the visible (ATSR and MODIS) and the infrared (IASI ULB8) for both, the tropospheric and the stratospheric setup of EMAC.

- Sophisticated modeling of dust and organic aerosol as well as a detailed volcano data set reproduce (aerosol) extinctions in the lower stratosphere observed by GOMOS at three different wavelengths (Bingen et al., 2017).

- Simulated total AOD in the mid-visible is very sensitive to aerosol water and composition of sea salt. In the modal model the bulk fraction has to be increased compared to ions to reduce artifacts. The satellite data help to find the best parameters.

- There is a need for updated emission inventories of pollutants (esp. SO₂)

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9 TEMPORAL TRENDS IN NATURAL COARSE-MODE AOD

Summary
In this section of the report the long-term AOD (total, fine mode and coarse mode) time-series of the entire ATSR climate record based on three different retrievals are examined for significance of temporal trends. This is explored for selected regions and for the globe using standard statistical methods for trend detection. A particular focus is put on the potential of the ATSR record to also detect coarse mode aerosol trends. For just the AATSR sensor period (2003-2011) significant positive trends for total AOD over the mid-East and S-Asia are detected, consistent with MODIS trends in those regions. The entire ATSR data involves two different sensors (ATSR-2 1996-2002, and AATSR 2003-2011). With the extended time period more trends appear as significant, most prominently AOD decreases over Europe, AOD decreases over land, often associated with decreases in AODf. However, due to discontinuities in the two-sensor data record with respect to calibration and spatial coverage interpretations of total data records trends are more uncertain. AOD trends over ocean areas are inconclusive among the different ATSR retrievals. Coarse mode AOD (AODc) as the difference of an AOD retrieval and an aerosol model based AODf estimate involves two uncertainties and thus AODc trends are more difficult to extract. The most consistent AODc trend appears over South Asia, where all three ATSR retrievals indicate small AODc increases. Other component AODc trends are often inconsistent among the different retrievals and indicate methodological problems. Possible future research may explore further, whether the data from the two sensors (ATSR-2 and AATSR) can be better aligned, whether calibration and retrieval choices are responsible for trend artefacts or whether other data support the satellite AOD trends across the two sensors.

ANALYSIS
Recent analysis of trends in AOD (AERONET, MODIS, MISR, SeaWIFS) have demonstrated the continued shift in fine-mode aerosol maxima from the EU and the US to south-east Asia (for instance Hsu et al., 2012; Zhang and Reid, 2010, Xia, 2011, Chin et al. 2014). Coarse mode (dust) aerosol exhibited increases east of the Sahara (e.g. Arabian Peninsula) and decreases west of Africa (Atlantic outflow). The authors suggest that longer periods are needed in many regions to establish significant trends, something which is possible to achieve with combined ATSR-2/AATSR time series. Coarse mode aerosols represent mainly natural aerosols and account for more than half of the global AOD. Global AODc trends may reflect a major climate feedback process, linked to changed winds or land cover.

Earlier work (Aerosol_cci2 PVIR, v3.4) showed that so far insufficient ground data are available to fully validate or invalidate long term trends found in combined ATSR-2/AATSR time series. Changing and increasing AERONET network coverage as well as missing satellite data in the early period of ATSR-2 and in the overlap period ATSR-2/AATSR make a full validation for the trends a challenging task. Such validation requires more studies not feasible here. We study the problem by including only satellite data, do a robust standard statistical trend analysis for averages from large regions, use all three ATSR-2/AATSR retrievals, compare also to MODIS data in the period 2003-2012, exclude years with incomplete ATSR-2/AATSR satellite data coverage and compare coarse mode AOD trends with total and fine mode AOD trends in a consistent way. Regions as exemplary shown in Figure 9.1, are filtered with a land/sea mask following the HTAP2 convention (see Galmarini et al. 2017), so that marine and land areas are not mixed into one region, except for “global”.
The significance of trends is established using standard practice as established by TFMM (UN-ECE EMEP task force on measurements and modelling) and WMO. In that procedure a minimum of 7 years of data and 70% coverage of the trend period is required. The basis for our trend calculations are yearly means, derived from seasonal mean of all retrieval data per region (1x1 degree daily gridded Aerosol_cci standard product data). For the years 1996 to 2002 data from the ATRS-2 instrument is used, for the years 2003 to 2011 the data from AATSR. The year 2012 was omitted because the data record stops in April. The global data, seasonal averages and annual means are shown in Figure 9.2.

*Figure 9.1* regional sub-area choices for North America, Europe, South Asia and East Asia. Year 2010 AODf average maps by the ATSR Univ. Swansea retrieval depict the exact area boundaries
Figure 9.2: Time-series of global total AOD for annual averages (top row) and for seasonal averages (bottom row). The left panel presents data of three different ATSR retrievals for the entire ATSR data records based on ATSR-2 sensor data (1996-2002) and AATSR sensor data (2003-2011). The right panel compares the three ATSR retrievals for AATSR sensor data only with retrievals from MODIS.

The non-parametric Mann-Kendall test has been used for detecting and estimating trends. The Mann-Kendall test has become a standard method when missing values occur and when data are not normally distributed (Tørseth et al., 2012; Colette et al., 2016). A value of 90% (p-value below 0.10) has been chosen as the criteria for determining the significance of a trend. The Theil-Sen’s slope estimator has been used to quantify the magnitude of trends (Gilbert, 1987) in AOD units. For simplicity we report here relative trends. The relative trend (tr) is computed from the absolute value of the trend per year (t) normalized by the initial value (ci) of the time series and is given in percent per year (tr = t/ci).

The quantitative trend analysis is reported in Tables 9.1 and 9.2 for 6 major regions, and separately for ocean and land areas and for the entire globe. Only significant trends are transferred into the tables. Table 9.1 compares for the entire ATSR-2/AATSR period (1996-2011) trends of three ATSR retrievals for total AOD and its fine-mode (AODf) and coarse-mode (AODc) components. Table 9.2 compares total AOD trends for the entire ATSR-2/AATSR period (1996-2011) with those for the
AATSR period only (2003-2011). For the shorter AATSR period derived significant trends for total AOD by MODIS are given for comparison.

**Table 9.1:** Significant trends (90% confidence interval) in total AOD, AODf and AODc based on three retrievals (SU - SU 4.3, FI - ADV 2.3-plume, OX - ORAC 4.01) for the entire ATSR record (1996-2011). See text for methods. Significant trends where at least 2 ATSR retrievals agree, are given in bold.

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<tr>
<td>% / year *</td>
<td>SU   FI  OX</td>
<td>SU   FI  OX</td>
<td>SU   FI  OX</td>
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<tr>
<td>Middle East</td>
<td>3.0   1.6</td>
<td>0.8</td>
<td>13.0</td>
</tr>
<tr>
<td>N. Africa</td>
<td>-1.6</td>
<td>-1.7 -1.3 -0.8</td>
<td>-1.5 -2.6 -2.0</td>
</tr>
<tr>
<td>S. Asia</td>
<td>1.7   1.8 1.1</td>
<td>7.2</td>
<td>9.9 10.0</td>
</tr>
<tr>
<td>E. Asia</td>
<td>0.8</td>
<td>-0.6</td>
<td>1.5 5.9</td>
</tr>
<tr>
<td>N. America</td>
<td></td>
<td></td>
<td>2.1</td>
</tr>
<tr>
<td>Europe</td>
<td>-1.0 -1.3</td>
<td>-1.4 -1.6 -0.7</td>
<td>-1.1 1.2</td>
</tr>
<tr>
<td>Ocean</td>
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<td>-3.3</td>
<td>-1.1 1.2</td>
</tr>
<tr>
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</tr>
<tr>
<td>World</td>
<td>-0.9 -1.0</td>
<td>-1.0 -2.7</td>
<td>-1.2 1.5</td>
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* trends in % are less meaningful if the reference value is small.

**Table 9.2:** Significant trends (90% confidence interval) in total AOD based on three retrievals (SU - SU 4.3, FI - ADV 2.3-plume, OX - ORAC 4.01) for the entire ATSR record (1996-2011) and for only the AATSR record (2003-2011). For the shorter AATSR period also trends of MODIS (MO - MODIS collection 6, terra) are given for comparison. See text for methods. Significant trends where at least 2 ATSR retrievals agree are in bold.

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<tr>
<td>% / year</td>
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<td>Middle East</td>
<td>3.0   1.6   2.2</td>
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<tr>
<td>S. Asia</td>
<td>1.7   1.8 1.1</td>
<td>1.0 1.8 1.8 1.6</td>
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<tr>
<td>E. Asia</td>
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<td>N. America</td>
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<td>Europe</td>
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<td>Ocean</td>
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<td>Land</td>
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<tr>
<td>World</td>
<td>-0.9 -1.0</td>
<td>0.7</td>
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For the shorter AATSR period only few significant regional trends for total AOD are identified, as indicated in Table 9.2. However, the positive ATSR trends for total AOD in the Middle East and South Asia (which includes part of the Arabic Peninsula) are supported by trends of MODIS data.

For the longer ATSR-2/AATSR period there are more significant trends. Positive trends are found over South Asia, East Asia and the Middle East for both total AOD and AODc. The trend identification over North Africa as function of size is unclear, possibly because the SU retrieval misinterprets dust size, attributing too much AOD to AODf. Globally, as well as over land and ocean regions combined, there a small decreasing trend but these trends should be viewed with caution since inconsistencies between ATSR-2 and AATSR data, as revealed during the overlap time may create trend artefacts. For Europe the negative trend for total AOD is related to AODf and not to AODc.

The large positive trends for AODc for South and East Asia in Table 9.1 deserve more inspection, see Figure 9.3.
Figure 9.3: Time-series of the three ATSR retrievals for AODc in East Asia (left) and South Asia (right). AODc is based on differences between retrievals for AOD and AODf. Derived trends for the entire period as indicated, but AODc trends would disappear if only AATSR data were considered.

It may be suspected that the suggested large positive trends for AODc are driven by differences between ATSR-2 (before 2003) and AATSR (after 2002) data, in particular in estimating fine (and implicitly coarse) mode components of AOD. Note in that context that the coverage by ATSR-2 was worse with no coverage in some parts of the regions. If only data of the AATSR time-series (2003-2011) were no significant AODc trends are found.

Major results on AOD trends from the entire ATSR climate data record on AOD are:

- longer time-series spanning several decades and more capable satellite sensors for more accurate retrievals are needed to obtain consistent trends for aerosol properties
- careful data understanding of biases (especially during sensor and platform changes) and more research is still required in order to consolidate trend understanding
- positive AOD trends of AATSR (2003-2011) in the Middle East are consistent with retrievals by AODc trends MODIS (and ground-based AERONET data)
- AODc trends near dust sources are inconclusive probably due to small trends, inter-annual variability and ATSR retrieval accuracy limitations to detect dust over bright surfaces.
- The negative total AOD trend over Europe is associated with reductions to the fine mode AOD (AODf) - without statistically significant changes to the coarse mode AOD (AODc)

REFERENCES


Zhang, J.; Reid, J. S., A decadal regional and global trend analysis of the aerosol optical depth using a data-assimilation grade over-water MODIS and Level 2 MISR aerosol products. Atmos. Chem. Phys. 2010, 10 (22), 10949-10963.
10 AEROSOL-CLOUD RELATIONS IN SATELLITE DATA

SUMMARY

Monthly statistics of associated aerosol and cloud properties are combined to establish relationships. For lower altitude water clouds the relationships between aerosol number (via AODf) and cloud drop number concentrations (CDNC) aerosol are examined with the hypothesis that with more available condensation nuclei droplet concentration should be higher (with the consequence that clouds become more reflective). Indeed associations of the most reliable AODf and CDNC retrievals reproduce this dependence, but the dependence is much smaller than assumed in most global models. For higher altitude clouds the relationship between dust AOD and cloud cover was investigated with the hypothesis that with more dust (as aerosol particles with dust are preferred nuclei) the ice-cloud cover increases as dust aerosols are preferred ice nuclei. The correlation results however are rather diverse and inconclusive.

OBSERVED RELATIONSHIPS

Satellite retrievals of aerosol and cloud properties are often uncertain. Still in a relative sense these data offer valuable information, through relative changes and interproduct relationships. Now these relationships also depend on observing scales. For instance, the impact of ship exhaust on the brightening of low altitude cloud is much stronger on local scales than on scales of global modeling (ca 100x100km). Thus to constrain simulated relationships in global modeling, associations of retrieval averages at a coarse 1x1deg longitude and latitude spatial resolution are investigated (- although it is understood that any revealed relationship does not necessary prove a direct causality). Here relationships of aerosol to two cloud types are examined. For low altitude water clouds, relationships between aerosol number (via AODf) and cloud drop number concentrations (CDNC) are examined with the hypothesis that droplet concentrations should be higher with more available condensation nuclei. For higher altitude clouds the relationship between dust AOD and ice cloud cover or ice cloud optical depth was investigated with the hypothesis that with more dust aerosol associated ice nuclei, the ice-cloud cover and/or ice-cloud optical depth are expected to increase.

aerosol and water clouds

There are many pathways in which way aerosol can influence and modify water cloud properties. Probably the most influencial aspect is that aerosol particles can act as nuclei on which cloud-droplet can form during condensation. For the same amount of water vapor available at the time of condensation, more and smaller droplets form if more cloud nuclei from aerosol are available. Since a cloud with smaller droplet sizes has a stronger solar reflection than a cloud with the same water content but larger droplet, more solar energy will be lost to space (e.g. extra aerosol from ship exhaust locally brightens lower altitude water clouds over oceans along the ship’s path, so called ‘ship tracks’). Both MODIS and ATSR sensor retrievals offer estimates for AODf and CDNC. Note that AODf is a column property, but since (1) tropospheric aerosol is concentrated in the lower troposphere (near water clouds) and (2) smaller aerosol sizes largely determine the aerosol number, AODf can be used as a good proxy for aerosol concentrations near water clouds. In order to assure higher quality retrievals, associations were limited to (1) ocean areas only (where the underlying solar reflectance retrievals are more reliable due to a relatively dark background), (2) overcast cloud conditions and (3) AODf larger than 0.05 (as smaller AODf values are highly uncertain). In order to achieve statistical relevance all relationships are combined in a single plot (hereby surrendering seasonal and regional dependencies for sufficient statistics). The probability distributions in AODf and CDNC space are presented in Figure 10.1 for different CDNC retrievals based on MODIS sensor data over the entire year (Bennertz, Grosvenor and Woods) and for just the boreal summer season based an ATSR sensor data for just the boreal summer season (Christensen). Also presented in the four panels of Figure 10.1 are logarithmic curve best fits through the CDNC median values of AODf bin statistics in the form of CDNC = a * exp (-b *AODf +1). While there are differences in retrieved background CDNC values (values in the individual best fits for ‘a’ differ) all average relationships suggest the same incremental change (as values in the individual best fits for ‘b’ are almost identical, so that a median value of 1000.0 was picked ).
**Figure 10.1:** AODf vs CDNC relationships using monthly 1x1 lat/lon retrieval averages of two different CDNC retrievals with MODIS sensor data (upper row) and the same relationship only with data for the boreal summer of MODIS and ATSR sensor data (lower row). The probability frequency is indicated by the color and by AODf bins data are summarized by average (*), median (−) and uncertainty (boxes establishing 25th and 75th percentiles and whisker ends 10th and 90th percentiles). Functions of best fit logarithmic curves are presented at the top right corner of each panel.

Thus for different satellite sensors based retrieval relationships – and apparently independent of the season –, same incremental AODf increases (e.g. above a non-zero AODf background) yield identical factor increases to the CDNC concentration of a water cloud. These ‘observed’ increases to CDNC are much weaker than prescribed CDNC increases in most models, as shown in Figure 10.2.

**Figure 10.2:** as in Figure 10.1 comparing averages of observations (left) with global modeling (right)
The ‘b’ value of the curve fit (indicated in the upper right corner of each panel in Figures 10.2) is much smaller in global modeling, if accumulating model suggested relationships at only those ocean locations/months where satellite data based relationships were available – using the model output of seven different models participating in AeroCom experiments. This smaller value ‘b’ means that the same incremental change AODf change leads to a much stronger factor increase to the CDNC. Thus, the aerosol associated cloud albedo increase in modeling effect is much stronger than (satellite) observation suggest. The observation based CDNC change when applied to cloud microphysics of a cloud properties (optical depth, cloud cover) of a cloud climatology in an off-line radiative transfer code (Stevens et al., 2015) yields the seasonal indirect aerosol forcing patterns of Figure 10.3.

Figure 10.3: Seasonal distribution patterns for the (first= smaller cloud drop size, same water content) indirect aerosol effect (by today’s anthropogenic aerosol) based on satellite based relationships between AODf and CDNC along with estimates for AODf at pre-industrial times from modeling.

The global annual average by today’s anthropogenic aerosol to water cloud microphysics (that is the reduction to cloud drop size), as illustrated in Figure 10.3, yields a global annual average for the aerosol indirect forcing of about -0.9W/m². This is much smaller than in most global models. This approach is admittedly simple. However, the use of monthly average seems justified as the AODf vs CDNC relationship are not significantly different at higher temporal (e.g. daily) resolution. Also the surrender of the regional dependence and of aerosol altitude specifics (which could not be accounted by using column average for aerosol) does not seem to matter, as more advanced simulations, that consider these dependencies yields almost the identical indirect forcing strength and patterns of Figure 10.3. Admittedly this approach is much simpler than the detailed investigation of Chapter 5 between aerosol (via the AODf similar aerosol property) and cloud properties (there not just the aerosol first indirect effect). However, chapter 5 interprets observations by global modeling (e.g. stratification of cases through modeling), while this approach focuses just on available observations.
aerosol and ice clouds

Poorly understood is the impact of aerosol on ice-clouds, in part as aerosol concentration in the upper troposphere are much lower than at the surface. It is however known that mineral dust aerosol particles are preferred ice-nuclei. In-situ investigation on mountains reveal that most (heterogeneously formed) ice crystals contain dust or an aerosol type mixture with dust. Also significant dust amounts can relatively easy reach near dust sources, where the aerosol lifetime is much longer than near the surface. And observations in regions of dust outflow off continents (e.g. west of North Africa onto the Atlantic) usually observe a higher frequency of cirrus clouds when atmospheric mineral dust loads are higher. As IASI retrieves larger mineral dust particles as well as higher altitude cirrus clouds, these retrievals seem well suited to test connections with dust AOD and cirrus cloud properties. Annual averages for dust AOD (at 550nm) and cirrus cloud cover by IASI retrievals for the year 2009 are presented in Figure 10.4.

![Figure 10.4: global distribution of annual mineral dust AOD and ice cloud cover averages by IASI](image)

The initial investigation addresses cloud cover. Hereby monthly 1x1 degree lat/lon data correlations for mineral dust AOD and (ice) cloud cover are investigated within 12/6 degree lat/lon subregions. The resulting sub-regional correlation coefficients for each month are presented in Figure 10.5. The result is very noisy. Both positive and negative correlations are detected of next to each other. At least the overall average correlation tendency is weakly positive. Similarly noisy (not shown) are correlation plots between dust AOD and either ice water content of ice cloud optical depth. More detailed studies are required which remove cases with low (and noisy) values, explore smaller temporal scales (to better address the dust plume like behavior) and also larger spatial scales and also applies available IASI information on cloud altitude.

While these initial results are somewhat disappointing, there are certainly also explanations that higher dust loading dust can be related to fewer clouds, as dust has an extended lifetime in areas without clouds. In any case the IASI data-set is a nice data-set that provides associations between aerosol and cloud properties. And these IASI associations deserve to be investigated.

Major results on observation relationship

- different satellite sensors (e.g. MODIS, ATSR) agree a on positive logarithmic relationship between aerosol number and water cloud droplet number
- the effect by anthropogenic aerosol on the microphysics of water clouds when applying satellite (ATSR, MODIS) based relationships between fine mode AOD (AODf) and Cloud Droplet Number Concentration (CDNC) retrievals translates into an indirect TOA forcing of - 0.8 W/m2, much smaller than in most global models.
- IASI retrievals for both large size mineral dust and (ice-) clouds – even as function of altitude are a potential testbed to extract observational relationships between elevated (dust) aerosol and ice-clouds

- initial investigations of correlations between mineral dust on (ice-) cloud cover are highly variable and overall positive, but not as strong as expected

**Figure 10.5:** monthly distribution of correlation coefficients between (mineral dust) AOD and retrieved high altitude cloud cover with the IASI sensor for the year 2008. The value below the label indicates the average correlation coefficient.

**REFERENCES**


11 HIGHLIGHT SUMMARY

TRENDS
- globally a weak positive trend of fine mode AOD (but no trend for total AOD) over the length of the entire 17 year data record (after overlap adjustments) is detected by two ATSR (SU, FI) retrieval time series

- globally a shift to smaller aerosol sizes globally is suggested as a weakly negative trend to coarse mode AOD is deduced while fine mode AOD slightly increases

- over the time of the ATSR climate data record regional shifts in fine mode AOD from Europe and northern America to southern and eastern Asia are detected. These shifts are consistent with known regional changes in anthropogenic emissions, but the shifts are smaller than simulated by global modeling

- inconsistencies between ATSR-2 and AATSR sensor regional averages during the overlap period need to be adjusted before any analysis; as conservative alternative trend analysis of only the (shorter) AATSR sensor period (2003-2010) can be conducted, which is too short for confident trend predictions. The needed overlap adjustment is difficult and such an adjustment also varies for different retrieval approaches even in sign and also for total AOD and AODf.

- Detecting coarse mode AOD (AODc) trends is generally difficult - especially the AODc values are low. ATSR capabilities to detect trends for AODc are limited suffer from large uncertainty, as AODc data are based on differences (AODc = AOD – AODf), thus involves two uncertainties.

- general ATSR retrieval accuracy issues remain as indicated by significant differences to expectations by global modeling (represented by a best knowledge climatology from a multi-model model median absolutely scaled with ground-based AERONET measurements), especially over continents

- one obvious strength of the ATSR data record is the capability to document regional and seasonal AOD anomalies.

- ATSR is highly sensitive to pollution and wildfire which are major contributors to total AOD and fine mode AOD variability. Regional anomalies indicate that this variability has decreased, in part since wildfire seasons (especially over S. America) are less intense than in the 90ies

- longer time-series spanning several decades are needed (e.g. SLSTR data to extend the AATSR data record) to obtain consistent trends for aerosol properties; more capable sensors (higher number of independent observables) help reduce this required period.

- careful data understanding of biases (especially during sensor or platform changes) is required in order to avoid misleading interpretations of trends

- positive total AOD trends of AATSR (2003-2011) in the Middle East are consistent with retrievals by coarse mode AOD trends of MODIS (and ground-based AERONET data), but apparently the AATSR size attribution of AOD is incorrect as no significant coarse mode AOD trend is derived

- coarse mode AOD trends near dust sources are inconclusive due to inter-annual variability and ATSR accuracy limitations to detect dust over bright surfaces
CLOUD AEROSOL INTERACTIONS

- different satellite sensors (e.g. MODIS, ATSR) agree on positive logarithmic relationship between aerosol number and water cloud droplet number
- the effect by anthropogenic aerosol on the microphysics of water clouds when applying satellite (ATSR, MODIS) based relationships between fine mode AOD (AODf) and Cloud Droplet Number Concentration (CDNC) retrievals translates into an indirect TOA forcing of -0.8 W/m², much smaller than in most global models.
- IASI retrievals for both large size mineral dust and (ice-) clouds – even as function of altitude are a potential testbed to extract observational relationships between elevated (dust) aerosol and ice-clouds
- initial investigations of correlations between mineral dust on (ice-) cloud cover are highly variable and overall positive, but not as strong as expected
- liquid water path relationship to aerosol number [dln(LWP)/dln(AI)] in modelling is affected by aerosol water uptake in humid environments around clouds
- the AATSR and MODIS associations of an improved cloud aerosol pairing algorithm (CAPA, Christensen et al., 2017) minimizes this water uptake biases and reduces effects by cloud contamination, aggregation or 3D effects
- the (diagnosed) removal of aerosol water in global modelling resulted in a weaker liquid water path relationship to aerosol number [dln(LWP)/dln(AIdry)] (more like satellite observations)
- AATSR data suggest no cloud top entrainment for non-raining scenes (unlike MODIS – possibly related to how precipitation is diagnosed or differences in sampling)

MODELING

- simulated dust AOD distributions generally agree with the satellite data in the visible (ATSR and MODIS) and the infrared (IASI ULB8) for both, the tropospheric and the stratospheric setup of EMAC.
- sophisticated modeling of dust and organic aerosol as well as a detailed volcano data set reproduce (aerosol) extinctions in the lower stratosphere observed by GOMOS at three different wavelengths (Bingen et al., 2017).
- simulated total AOD in the mid-visible is very sensitive to aerosol water and composition of sea salt. In the modal model the bulk fraction has to be increased compared to ions to reduce artifacts. The satellite data help to find the best parameters.
- there is a need for updated emission inventories of pollutants (esp. SO₂)
- ULB IASI retrievals yield strongest assimilation benefits over the forecast
- IASI retrievals tend to produce an analysis that underestimates dust AOD near source regions, with the exception of MAPIR retrievals which produce an overestimation of dust AOD everywhere
- further studies are needed to optimally characterize observation uncertainty for IASI data assimilation

LONG TERM DATA RECORD
- The UV-AI long term data-record composed from different sensor data is relative stable
- The UV-AI provides (only) qualitative information on elevated aerosol absorption
- Applications over central Africa and southern America regions with seasonal wildfire activity reproduce the seasonality of elevated aerosol absorption very well
- The interpretation of inter-annual variability and even trends in terms of wildfire intensity is limited
- The use of the UV-AI data records by the climate modeling community is not straightforward and requires a use of the observation operator (UV-AI simulator)

RADIATIVE FORCING
- the ATSR AOD climate data record (1996-2011) reveals aspects on regional variability
- direct aerosol radiative effects have a strong regional and seasonal character
  - TOA net flux (defined as downward – upward flux): large increases over deserts, losses (-) over oceans: -0.9 W/m2
  - surface net flux: losses in regions with larger AOD / smaller sizes: - 4.5 W/m2
  - energy loss is larger at clear-skies: TOA : - 2.2 W/m2 / surface: - 5.4 W/m2
- to put it into perspective, bottom-up global modeling (via emission data) tells us that today’s anthropogenic aerosol mainly contributes via the fine-mode AOD. In terms of total AOD today’s anthropogenic aerosol has only raised the total AOD by 30% but the aerosol number on average has increased by 50% ( → big potential to modify clouds)
- based on the from modeling predicted fine-mode anthropogenic AOD contribution:
  - anthropogenic direct TOA net flux loss: - 0.2 W/m2 (all) / - 0.6 W/m2 (clear)
  - anthropogenic indirect TOA effects are larger and uncertain: -0.5 to -1.0 W/m2
- clouds affect clear-sky TOA net flux loss by anthropogenic aerosol in different ways
  - cloud over aerosol (aerosol effects are reduced) → smaller losses
  - aerosol above clouds (brighter background for aerosols) → smaller losses
  - brighter clouds (as more aerosol reduce drop size) → larger losses
  - overall clouds are likely to increase clear-sky forcing (from -0.6 to ca -1.0 W/m2)
12 APPENDIX

ATSR data-set consistency and anomalies

ATSR data were processed covering the entire ATSR-2 (1995-2003 on ERS1) and AATSR (2002-2012 on ENVISAT) data record. Thus, 16 complete years (1996 to 2011) are covered. Global maps of annual anomalies (in reference to the 2008 to 2011 average) are shown for AOD and AODf (at 550nm) four different ATSR retrievals (SU v4.2, FI v2.3-plume, OX v.3.02 and O4 v4.01) applied to the same data. The four anomaly maps are presented retrievals in Figures A1 to A4.

The figures nicely reveal known wildfire anomalies, which show up in both AOD and AODf data (since wildfire aerosol particles are relatively small). These wildfire anomalies are produced by all retrieval approaches, but at different strength. Most notable are anomalies over South America (biomass burning was there generally stronger in the late 1990ies and relative peak seasons occurred in 1997, 2004, 2005 and 2007), over Indononesia (1997), over Siberia (1996, 2003), over Alaska (2004) and near Moskow (2010). In contrast, the retrievals failed to clearly identify the from emissions data expected shift in regional pollution via AODf (away from Europe and the US to southern and eastern Asia), because the ATSR record is too short and further handicapped by inconsistencies between ATSR-2 (until 2002) and AATSR (from 2003) sensor data. Also known dust trends (strong increases over Arabia due to changes in meteorology, reduced outflow off western Africa) are not detected. This in part is caused that ATSR AOD retrievals do poorly over dust regions or even fail to retrieve (e.g. FI). Moreover, the AODc value of inferred from AOD and AODf retrievals (by default) and is usually much more uncertain. For investigations of trends for (dust) AODc, IASI retrievals seem more promising.

Investigating the global annual average numbers of the figures some indications on global AOD and AODf long-term changes are attempted (although it should be kept in mind, that the satellite data coverage is not globally complete and that AATSR coverage is better than ATSR-2 coverage). In order to establish changes between the early (1996 to 1999) and the later (2008 to 2011), differences between ATSR-2 (2000 to 2002) and AATSR (2003 to 2005) near the overlap time were subtracted. The resulting long-term changes for AOD and AODf are listed in Table A1. In that table also the range of annual averages for the initial four year (1996-1999) period and for the final four year (2008-2011) period are given for comparison.

Table A1. long-term changes of global annual AOD and AODf as suggested by the different (SU, FI, OX, O4) retrievals for the ATSR data-record (1996-2011), by taking the differences between 2008-11 and 1996-99 period averages after normalizing the retrievals to each other near the overlap time. The significance of these changes should be viewed in the context of the displayed interannual variability.

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<td>long-term change</td>
<td>-.002</td>
<td>+.001</td>
<td>.000</td>
</tr>
<tr>
<td>1996-1999 variability</td>
<td>.009</td>
<td>.007</td>
<td>.016</td>
</tr>
<tr>
<td>2008-2011 variability</td>
<td>.004</td>
<td>.002</td>
<td>.002</td>
</tr>
</tbody>
</table>

All data sets indicate a weak increase in AODf (+0.02 to +0.06) and a weak decrease in AODc (-0.00 to -0.03), with little change (and even different signs depending on the retrieval) to the total AOD. These long-term changes, however, are small compared to the inter-annual variability so that the long-term changes are not statistically significant. An interesting aspect is that the inter-annual variability (mainly caused by wildfire events) was much larger in the late 1990ies than in more recent years.

In summary, the entire data-record suffers from retrieval inconsistencies between the two (ATSR-2 and AATSR) sensors. Still, wild-fire anomalies are nicely reproduced, less so pollution shifts and anomalies associated with dust transport. Long-term AOD changes are small and insignificant although a shift to smaller sizes and reduced variability is indicated.
Figure A1: Annual anomalies for ATSR SU (version 4.3) retrieved AOD (top) and AODf (bottom), with respect to its 2008-11 average.
Figure A2: Annual anomalies for ATSR FI (version 2.30p) retrieved AOD (top) and AODf (bottom), with respect to its 2008-11 average.
Figure A3: Annual anomalies for ATSR OX (version 3.02) retrieved AOD (top) and AODf (bottom), with respect to its 2008-11 average.
Figure A4: Annual anomalies for ATSR O4 (version 4.01) retrieved AOD (top) and AODf (bottom), with respect to its 2008-11 average.
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