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ARTICLE

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Landsat time series reveal simultaneous expansion and intensification of irrigated dry season cropping in Southeastern Turkey

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ABSTRACT

Long-term monitoring of the extent and intensity of irrigation systems is needed to track crop water consumption and to adapt land use to a changing climate. We mapped the expansion and changes in the intensity of irrigated dry season cropping in Turkey´s Southeastern Anatolia Project annually from 1990 to 2018 using Landsat time series. Irrigated dry season cropping covered 5,779 km² (± 479 km²) in 2018, which represents an increase of 617% over the study period. Dry season cropping was practiced on average every second year, but spatial variability was pronounced. Increases in dry season cropping frequency were observed on 40% of the studied croplands. The presented maps enable the identification of land use intensity hotspots at 30 m spatial resolution, and can thus aid in assessments of water consumption and environmental degradation. All maps are openly available for further use at https://doi.org/10.5281/zenodo.4287661.

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Introduction

Irrigated agriculture boosts crop production through more intensive use of land, particularly in water-limited regions (Malek et al., 2018; Rosa et al., 2018). Water inputs enable cropland expansion on areas with insufficient precipitation, the introduction of additional crop types, a reduction of fallow years, or allow a higher frequency of cropping on existing cropland (Erb et al., 2013; Foley et al., 2011). However, inadequate management of irrigation systems and inefficient use of land and water resources are key problems in irrigated agriculture (Gerten et al., 2011; Jägermeyr et al., 2015). Specifically, in semi-arid to arid conditions, water-intensive crops and irrigation practices can lead to soil salinization (Singh, 2016). Long-distance water allocation increases seepage and evaporation losses, which adds to the risk of water scarcity (Mekonnen & Hoekstra, 2016; Porkka et al., 2016) and compromises irrigation-induced productivity increases (Rufin et al., 2018).

The spatial patterns, extent, and use intensity of many irrigated lands are currently not well understood (Ray & Foley, 2013), partly because statistics and reports are costly to produce and can be biased due to over- or underreporting of water use (Deines et al., 2019; Özdoğan et al., 2006). Cost-efficient monitoring of land and water resource use in irrigated production systems is urgently

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Supplemental data for this article can be accessed here.

needed. Remote sensing offers great potential for monitoring the extent and use intensity of irrigated agriculture across administrative borders, institutional settings, as well as management regimes (Löw et al., 2018; Özdoğan et al., 2010). Annual information on irrigated area extent at appropriate spatial resolution helps to understand the spatio-temporal patterns and trends of land-use intensity and can support land-use planning and policy towards attaining more efficient land and water resource use in water-limited production systems (Ambika et al., 2016; Chen et al., 2018).

Openly available remote sensing data support decadal analyses and monitoring of land cover and land use over large areas (Wulder et al., 2012; Zhu et al., 2019). The Landsat data record provides a suitable basis for such applications, as it spans more than three decades at 30 m spatial resolution with global coverage (Wulder et al., 2019). Cloud computing platforms such as Google Earth Engine (Gorelick et al., 2017) facilitate access to these data archives, thereby enabling remote sensing scientists to analyze large amounts of satellite imagery without the need for local server infrastructure.

In this context, land use mapping has substantially advanced through increased use of time series analysis techniques (Dong et al., 2019). Time series at the pixel-level can be statistically summarized as metrics that capture the distribution or variance of the spectral reflectance over a given period, commonly referred to as spectral-temporal metrics. Spectral-temporal metrics are increasingly used as a means to map land use at high thematic detail (Rufin et al., 2019; Wulder et al., 2018) and over long time frames (Dara et al., 2020; Deines et al., 2019). Spectral-temporal metrics in combination with state-of-the-art machine learning algorithms enable the production of multi-decadal land use maps in agricultural systems (Schmidt et al., 2016; Waldner et al., 2017). The resulting time series of land use maps can be translated into long-term land-use intensity indicators that reveal cropland expansion and intensification patterns, which in turn are essential for estimating water consumption in irrigated systems (Deines et al., 2019, 2017).

Turkey is the second-largest consumer of irrigation water amongst the Mediterranean countries due to the enormous demand in southeast Anatolia (Daccache et al., 2014). The region comprises Turkey´s largest regional development project, the Southeastern Anatolia Project (Güneydoğu Anadolu Projesi, GAP), which aimed at diverting and storing water from the Euphrates and Tigris rivers to irrigate 18,000 km^2 of arable land by 2005 (GAP, 2017). The envisaged completion of the GAP was delayed as parts of the infrastructure development were on hold due to geopolitical and socio-cultural disputes (Hommes et al., 2016). Currently, the operational areas of the GAP are mainly used to cultivate water-intensive crops during the dry summer months, mostly cotton and corn (Bilgen, 2018a; USDA, 2018). Cotton production is responsible for the major share of the Turkish irrigation water consumption (Daccache et al., 2014) and the water requirements for cotton in the semi-arid to arid GAP region exceed those of all other production regions of Turkey (Cetin, 2020; Ertek & Yilmaz, 2014). A better understanding of the patterns and trends of dry season cropping in Southeastern Anatolia is thus urgently needed, particularly in the face of future water shortages under a changing climate (Fader et al., 2016; Malek et al., 2018).

The objective of this study is to quantify the expansion and intensification of irrigated dry season cropping in the GAP region between 1990 and 2018 using Landsat time series. We address three main research questions:

(1) How has the extent of irrigated dry season cropping changed since 1990?
(2) What are the spatial patterns of dry season cropping frequency?
(3) How did land use intensity in terms of dry season cropping frequency change in the study period?

Data & methods

Study area

The GAP is a large-scale development project that covers 75,000 km^2 and accounts for nearly 10% of the Turkish land area across nine provinces in Southeastern Anatolia (Figure 1). The region has an arid to semi-arid climate with precipitation between 200 and 600 mm/year, while potential evaporation frequently exceeds 2,000 mm/year. The land and water resource program of the GAP comprises major infrastructure developments, including 22 dams for electricity generation and irrigation water provision, as well as 1,400 km of irrigation canal networks and tunnels. Two major tunnel systems deliver irrigation water from the Atatürk reservoir in Adıyaman province to the Harran and Ceylanpınar plains in Şanlıurfa since April 1995 (UNEP, 2004). The GAP was initiated by the Turkish State Hydraulic Works, with envisioned completion in 2005 (Bilgen, 2018b), but is currently still under development due to numerous delays (Kankal et al., 2016). In 2017, 5,459 km^2 (30% of the originally targeted area) were reported to be under irrigation (GAP, 2017).

Irrigation is essential for dry season cultivation due to the near-zero precipitation between July and September (Özdoğan et al., 2006). Until 1995, the region was dominated by the cultivation of winter and spring crops, such as wheat, barley, lentils, and chickpeas, which are commonly harvested until the end of June (Beaumont, 1996; Metin Sezen & Yazar, 2006). Dry season cropping expanded after the construction of the GAP irrigation infrastructure. The dominant crops grown in the dry season are cotton and corn (Özdoğan et al., 2006; Özerol & Bressers, 2017), hereafter referred to as dry season crops. The share of irrigated cotton cultivation increased drastically in the GAP region due to relatively low production costs and growing demand from the domestic textile sector (Solakoglu et al., 2013). Cotton covered 3,100 km^2 of the cropland in 2018, which corresponds to 56% of the national cotton production area (USDA, 2018). Dry season cultivation in semi-arid to arid conditions is extremely water-intensive, and the water requirements for corn and cotton production in the GAP region exceed those of other production sites in Turkey on average by 51% for corn and 182% for cotton (Cetin, 2020).

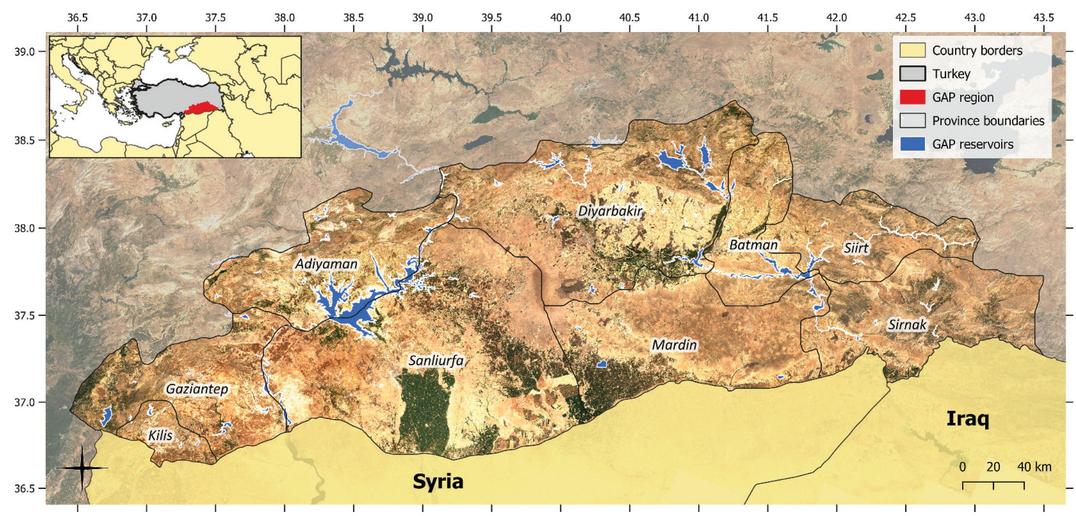

Figure 1. Location of the GAP region in Turkey (overview in the upper left corner). The main map shows a true-color satellite image (composited from Landsat ETM+ and OLI data) of August 2015.

Mapping dry season cropping

We produced 29 annual maps of dry season cropping for the period between 1990 and 2018 in several steps: First, we collected an extensive set of training data for 2015, a year with close-to-normal precipitation and temperature levels in the GAP region (Figure S1) and with high Landsat data availability (Table S1). Second, we trained a classification model based on these training data and spectral-temporal metrics for the year 2015. Third, we computed Landsat-based spectral-temporal metrics for each year between 1990 and 2018 and generated the maps using the 2015 classification model. Finally, we estimated classification accuracy, dry season crop area, and confidence intervals for each year using stratified estimation.

Training data

We targeted a binary class catalog consisting of dry season cropping (including double-cropped areas with harvests before the dry season crop) and one aggregate class for all other types of land cover or land use. The latter included water, non-vegetated land, grasslands, open to closed canopy shrublands and forests, winter crops (cereals and pulses), perennials (pistachio and olive trees), and fallow cropland. We collected training data as polygons with a minimum mapping unit of nine pixels (0.81 ha) and a maximum size of 30 ha using pixel-based Landsat composites (Frantz et al., 2016; Griffiths et al., 2013), a gap-filled time series of the Enhanced Vegetation Index (EVI) covering 2014–2016 (Rufin et al., 2019), and very high-resolution imagery available in Google Earth. We collected 568 training polygons across the GAP provinces, of which 37% represented dry season crops. We used all pixels located entirely within the polygons for model training (n = 10,780).

Spectral-temporal metrics

Spectral-temporal metrics are suitable to generate gap-free datasets over large areas, while at the same time providing information on land surface phenology. Spectral-temporal metrics have been widely used in large-area mapping applications in agricultural landscapes (Phalke & Özdoğan, 2018; Rufin et al., 2019; Waldner et al., 2017). We used Google Earth Engine (Gorelick et al., 2017) for producing a set of spectral-temporal metrics to discriminate dry season crops from the remaining land use and land cover classes in the GAP region. We used all available precision and terrain corrected images of the Landsat Collection 1 Surface Reflectance product acquired by the Landsat TM, ETM+, and OLI sensors (L1TP Tier 1), covering the growing season of the main dry season crops (July 1st to September 30th) in the GAP area for the years 1990 to 2018. This time window was defined according to the regional crop calendar (Figure 2), as it coincides with the maturity stage of dry season crops and has been shown to provide valuable information for Landsat-based mapping of dry season cropping amongst other cropping practices across Turkey (Rufin et al., 2019). Cloud, cloud-shadows, and snow were masked based on the cloud information contained in the Landsat Collection 1 quality bands (Zhu et al., 2015). We calculated band-wise spectral-temporal metrics that capture the distribution of reflectance values (25th percentile, median, 75th percentile, inter-quartile mean), and the variability of reflectance in the dry season (standard deviation and inter-quartile range) for each Landsat spectral band in the visible, near-infrared, and shortwave infrared wavelengths (totaling 36 features). For an overview of the number of images included and the average number of clear observations per year, please see Table S1.

Classification

We trained a Random Forest classification model (Breiman, 2001) based on the training samples and the spectral-temporal metrics of 2015. We used 250 trees and the square root of the number of input features at each split to identify the best feature. We subsequently used this classification model to classify all years, resulting in a time series of 29 binary maps covering the years 1990 to 2018. As irrigation infrastructure is a long-term investment, we eliminated pixels with only one year of dry

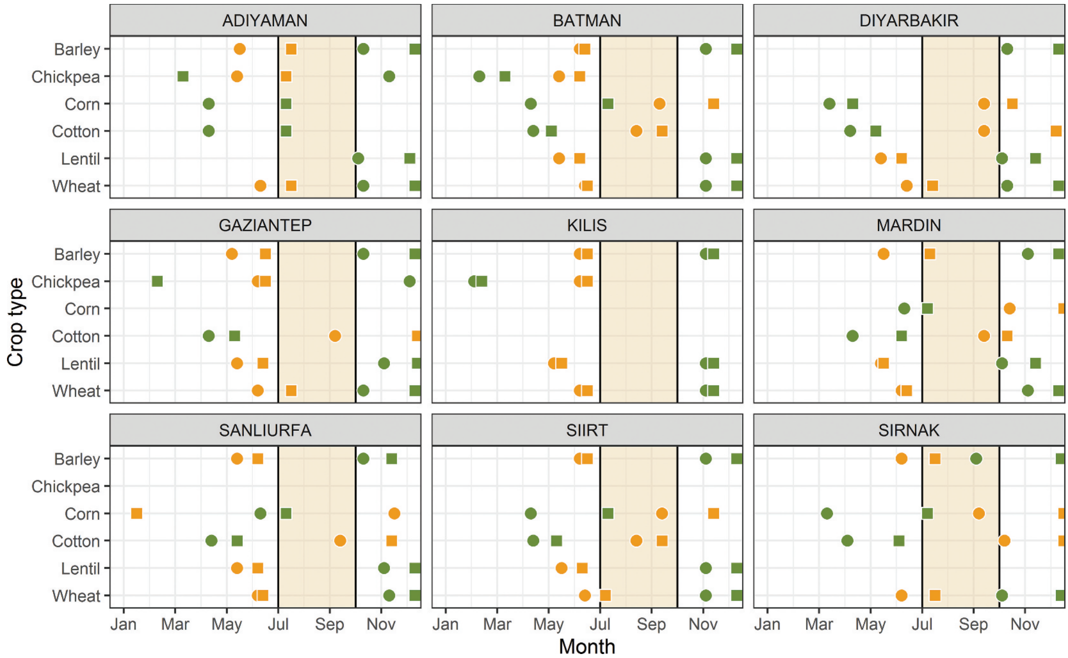

Figure 2. Regional crop calendar, indicating the start (circle) and end (square) of the planting phase (green) as well as the harvest period (orange) for six major crops in the GAP region. Yellow shading represents the time window for the inclusion of Landsat images. Data on the crop calendars were compiled from the Turkish Ministry of Agriculture and Forestry. Planting and harvesting dates were not available for all crops and provinces.

season cultivation over the study period for the subsequent analyses to reduce the effect of one-time commission errors on further analysis steps (Deines et al., 2017).

Estimating land use intensity

We performed a series of post-processing steps to capture land use intensity and its change at the pixel level (Figure 3). From the time series of maps, we derived the first year with dry season crops, the total number of years with dry season crops, and dry season cropping frequency (DSCF) as the percentage of all years with dry season crops after (i.e., excluding) the first year (Figure 3A). In the next step, we calculated long-term land use intensity indicators (Figure 3B). We calculated five-year dry season cropping frequency (5-year DSCF) for every year, which captures the share of years with dry season crops within a five-year moving window (accordingly only derived two years after the initial cultivation until 2016). Finally, we performed a pixel-wise linear regression using 5-year DSCF as dependent and time as an independent variable to identify linear trends in the 5-year DSCF. We limited this analysis to pixels with the first dry season crop before 2012 to ensure a minimum period of four years. The analysis yielded a spatially explicit representation of the linear regression coefficients, their standard error, as well as the statistical significance (p-values). We assessed the overall trend magnitude since the onset of dry season cropping as a proxy for intensification or dis-intensification. We included only significant trends ($p < 0.05$) with substantial trend magnitudes exceeding 25%, as absolute trend magnitudes below 25% were considered unsubstantial. We categorized significant and substantially positive or negative trend magnitudes into weak (25% to 50%), moderate (50% to 75%), and strong (75% to 100%).

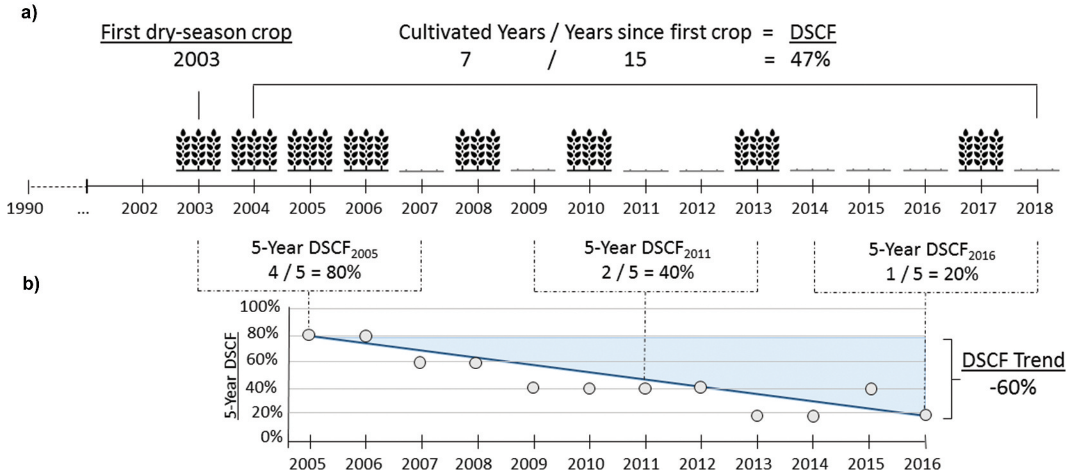

Figure 3. Schematic representation of pixel-level post-classification analyses. A time series of binary information on fallow or cultivated land was used to derive the initial cultivation year and DSCF (A), and 5-year DSCF, the linear trend in 5-year DSCF as well as the magnitude of the trend (B).

Accuracy assessment and area estimation

We used a stratified random sample of 1,260 Landsat pixels to estimate map accuracies and class areas. The validation sample size was estimated by targeting a 1% standard error of overall accuracy and assuming a 90% user´s accuracy for the dry season cropping and other classes (Cochran, 1977). As strata, we used a map of the initial cultivation year to cover different cropping periods, leading to 40 samples per year and 100 samples in permanent non-cropped areas. Each validation pixel was labeled as either dry season crop or other land cover using spectral time series plots and medoid composites of the growing season (Flood, 2013), assuming that crop cover prevails throughout most parts of this period (Özdoğan et al., 2006). We downloaded the composite time series using code produced for the TimeSync Legacy software (Kennedy et al., 2018) and visualized the composite time series in QGIS using the EO Time Series Viewer (Jakimow et al., 2020). To aid interpretation and to exclude potential areas of permanent vegetation, plantations, or seasonally inundated areas, we visually inspected each point location in very high-resolution imagery available in Google Earth.

Class labels for 179 samples could not be determined due to mixed pixel effects, i.e., where samples were located amidst neighboring parcels or in highly fragmented landscapes. We used the resulting 1,081 reference samples to estimate area-adjusted accuracies and error-adjusted area proportions of the dry season crop area for the entire GAP region (Olofsson et al., 2014; Stehman, 2014). We then calculated the first year of dry season cultivation, the number of years under dry season cropping and the DSCF for the reference samples to assess agreement between the map products and the reference data. We also calculated linear regression coefficients, R^2 and RMSE for the first year of cultivation, the total number of years under dry season cultivation, as well as DSCF. Finally, the dry season crop area for the entire region was estimated based on the reference samples. At the province level, we used the mapped area totals, due to an insufficient number of samples within provinces to allow for stratified estimation.

Results

Accuracy assessment

High map accuracies underline the robustness of our approach. Overall map accuracies ranged between 98.1% (± 0.8%) in 2009 and 99.8% (± 0.3%) in 1990 (Table S1). In most years, the omission (underestimation) of dry season crops tended to be higher than the commission (overestimation, Figure 4). The mean producer´s accuracy for dry season crops over the study period was 82.4% (ranging from 45.9% to 97.5%), and the mean user´s accuracy was 91.0% (ranging from 67.3% to 97.1%). The low producer´s accuracies of some early years partly corresponded with reduced data availability. However, other years with low data availability had high accuracies (e.g., 1990), and vice versa (e.g., 2009), and thus no clear relationship between data availability and accuracy was apparent (Table S2). It is noteworthy that our region-wide area estimates are unbiased as they were generated using a sample-based estimator.

We found high agreement between reference datasets and post-classification derivates (Figure S2), such as the total number of years under dry season cropping (β = 1.07, R^2 = 0.93, RMSE = 1.8 years). The most frequent errors were one-time commission on permanent non-cropland (n = 77), supporting the strategy of restricting analyses to regions with at least two years of dry season cropping. The mapped year of initial dry season cultivation was also highly correlated with the reference data (β = 0.922, R^2 = 0.85, RMSE = 3.4 years), similarly to the cropping frequency measure (β = 0.902, R^2 = 0.85 and an RMSE of 11.8%).

Expansion of dry season cropping

The start of the water transfer to Şanlıurfa and Mardin (cf. Figure 1) in 1995 marked the onset of dry season cultivation expansion in the GAP region. Our area estimates revealed a 617% increase in dry season cropped area since 1990 (Figure 5; top), from 935.53 km^2 (± 192.00 km^2) in 1990 to 5,778.87 km^2 (± 479.32 km^2) in 2018. The dry season cropped area increased with an annual rate of β_{year} = 170.86 km^2 (standard error 9.22 km^2, R^2 = 0.93), with deviations from this trend in 1995, 1998, 2007, and 2008.

Expansion occurred at varying rates in different parts of the GAP region (Figure 5; bottom) and concentrated in Şanlıurfa and Mardin throughout the study period, largely driven by the irrigation expansion in the Harran and Ceylanpınar plains. Expansion rates in Mardin increased drastically in the early and mid-2000s but declined in more recent years. Overall, the remaining provinces showed

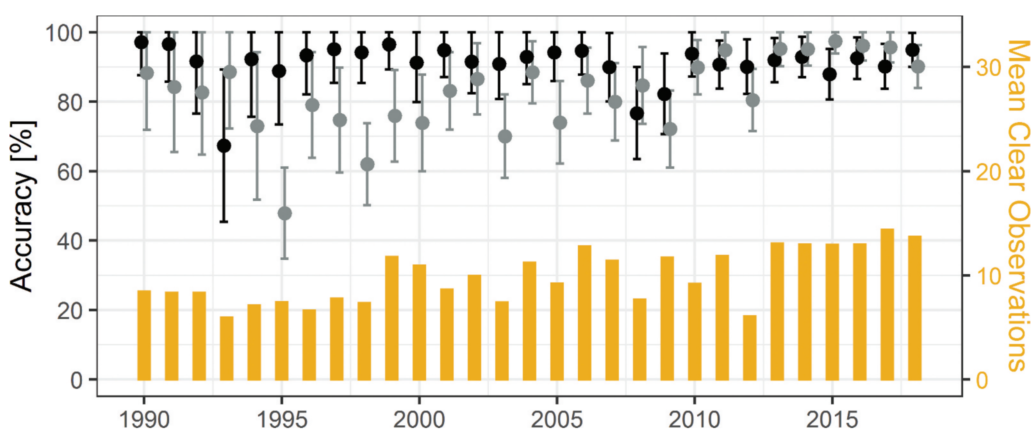

Figure 4. Estimates of user´s (black) and producer´s (grey) accuracy for summer crops. Error bars indicate 95% confidence intervals. Orange bars indicate the average number of clear sky observations in the respective year.

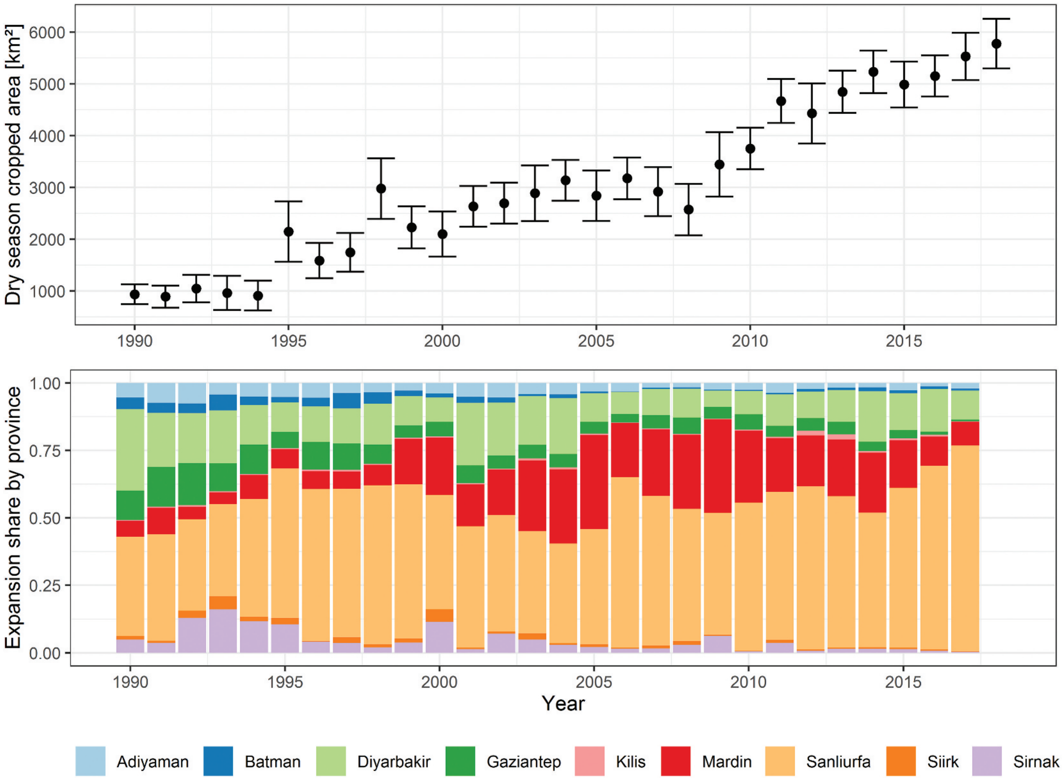

Figure 5. Annual dry season cropped areas in the GAP region between 1990 and 2018 with error bars indicating the 95% confidence intervals (top), and province-level shares of the total annual expansion (bottom).

declining expansion rates since the late 1990s and nearly halted in some of the western (Adıyaman, Kilis, Gaziantep) and eastern provinces (Batman, Siirt, Şırnak; Table S3).

Maps of the first dry season crop year reveal a detailed view of how dry season cropping expanded throughout the GAP provinces (Figure 6). In the first decade, dry season cropping was established mostly in Adıyaman (Figure 6A), Şırnak (Figure 6I), and Şanlıurfa´s Harran plain (Figure 6G). More recently, dry season crops expanded to Diyarbakır (Figure 6B), Gaziantep (Figure 6C), western and eastern Şanlıurfa (Figure 6),D,H and Mardin (Figure 6F). Large agglomerations of pivot-irrigated croplands replaced older rectangular parcels in the border region of Şanlıurfa and Mardin after 2010 (Figure 6E).

Patterns of dry season cropping frequency (DSCF)

Dry season cropping frequency (DSCF) expresses the percent of years with dry season cropping relative to all years after initial dry season cropping for each pixel. The average DSCF in the study region in the years after 1995 was 50.8%, with distinct variability between provinces. Mean DSCF was highest in Şanlıurfa with 57.4%, Mardin with 55.7%, and Diyarbakır with 42.7%, whereas all other provinces had a mean DSCF below 35%. The lowest mean DSCF was found in large distances to the main infrastructures of the GAP, namely the eastern provinces Siirk with 21.0%, Şırnak with 26.3%, and in the western province of Kilis with 26.0%.

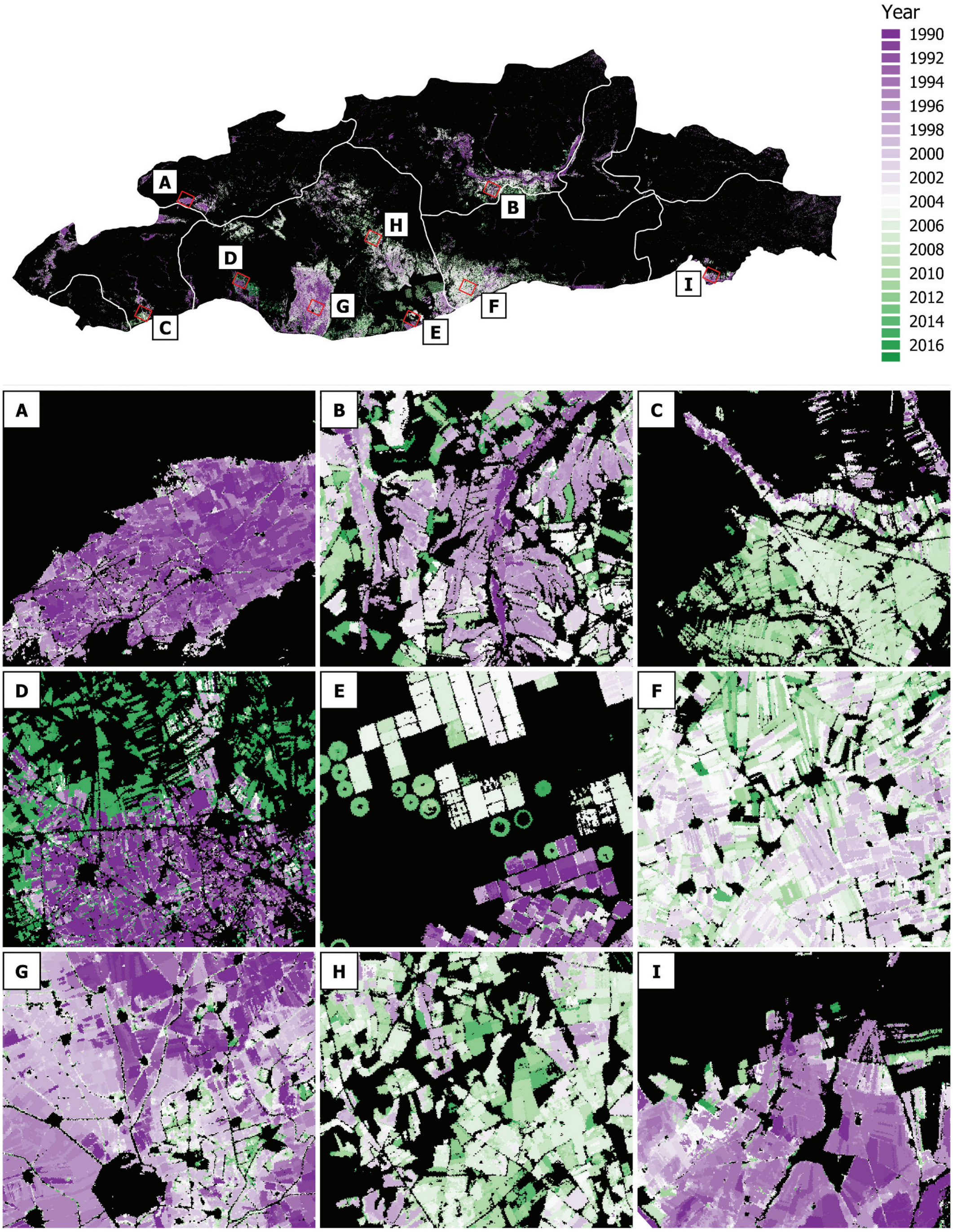

Figure 6. Maps of the first year of dry season cropping for the entire GAP region and selected areas.

A total of 6.6% of the area was cultivated during the dry season every year. We here considered a DSCF of 80% as a threshold for permanent cultivation (Deines et al., 2017). Following this definition, 15.6% of the croplands established since 1995 were permanently cultivated. On the contrary, 14.4% of the croplands showed a DSCF of less than 20%. The least and most intensively used 10% of the

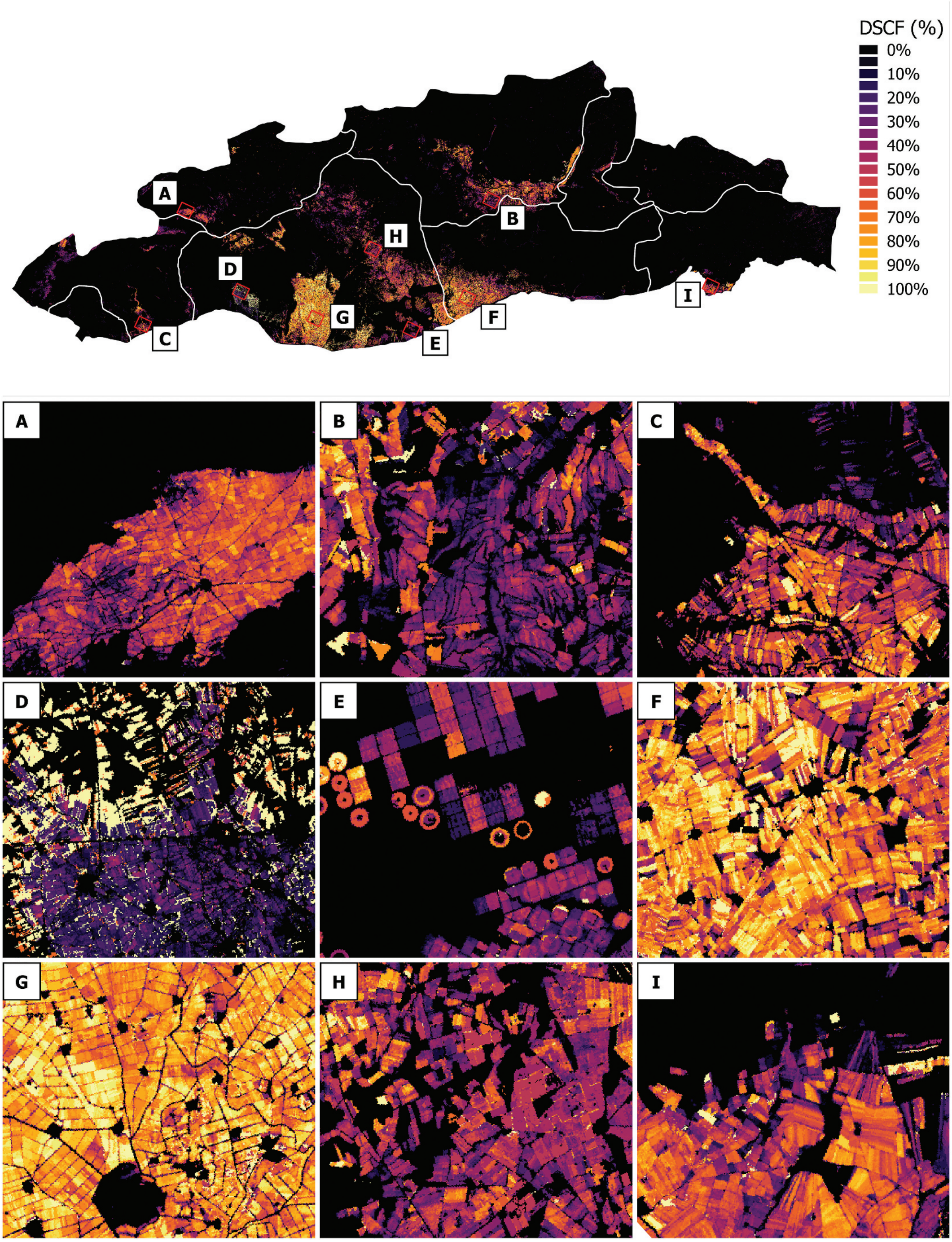

Figure 7. Fraction of years with dry season cropping after the initial cropping year (i.e., dry season cropping frequency, DSCF; in %).

study area each covered an area of 731.12 km^2 and had a cropping frequency of 13.6%, and 92.8%, respectively. Spatially explicit patterns reveal differences in cropping frequency across and within regions (Figure 7). DSCF was generally high in Şanlıurfa and Mardin. For instance, a DSCF above 80% was common in the Harran plain (Figure 7G), where some croplands exist since the mid-to-late

1990s. Likewise, croplands in western Mardin (Figure 7F) were frequently used. Intermediate DSCF of 40–80% occurred in Adıyaman and Şırnak (Figure 7 A, I), while lower DSCF occurred in eastern

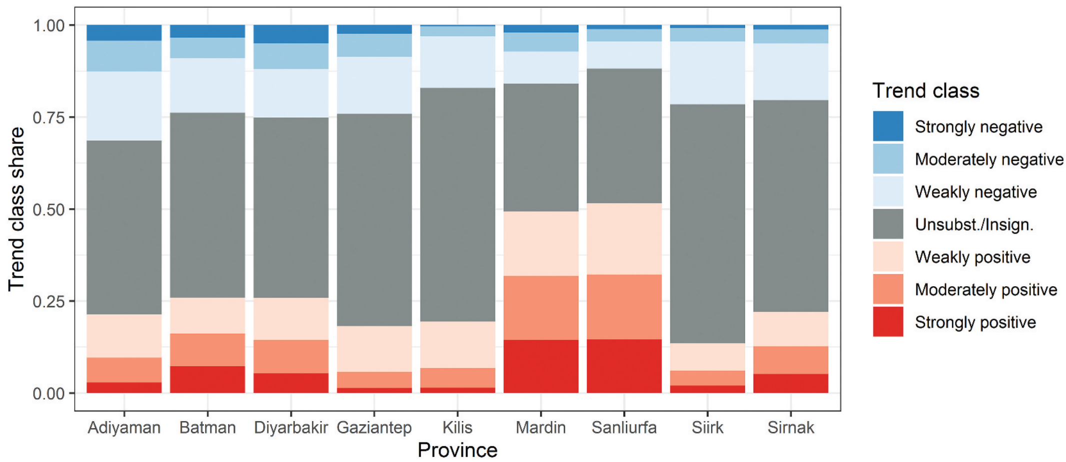

Figure 8. Province-level shares of trend class. The category 'Unsubst./Insign.' contains pixels with insignificant trends (p > 0.05) as well as those with magnitudes between −25% and 25%. For spatial patterns of DSCF trend magnitude and significance levels see Figures S 3 and S4.

Table 1. Trend magnitudes of five-year dry season cropping frequency.

Trend Magnitude	Class	Share of Cropland
< −75%	Strongly negative	2.2%
−50% – −75%	Moderately negative	4.8%
−25% – −50%	Weakly negative	10.5%
−25% – +25%	Insignificant/unsubstantial	42.5%
+25% – +50%	Weakly positive	15.9%
+50% – +75%	Moderately positive	13.7%
> +75%	Strongly positive	10.5%

Şanlıurfa (Figure 7 E, H) and Diyarbakır (Figure 7 B) where dry season crops were introduced more recently.

Trends of dry season cropping frequency

We calculated pixel-wise linear regressions of 5-year DSCF to identify areas in which substantial changes in cropping frequency occurred between the initial cultivation and the year 2016 (Table 1). The analysis revealed that 57.5% of the croplands underwent significant and substantial changes in cropping frequency over time. Negative trends were detected in 17.4% and positive trends in 40.1% of the study area, indicating that intensification processes dominated in the study period. On the contrary, 42.5% of the croplands in the study region did not show substantial trends.

Contrasting spatial patterns of trends in 5-year DSCF were visible at the province level (Figure 8). Intensification patterns dominated in Şanlıurfa and Mardin, where positive trends occurred on 50% of the cropland. The largest shares of dis-intensification were observed in Adıyaman, Batman, Diyarbakır, and Gaziantep, where negative trends occurred on one-quarter of the cropland or more. A strong local-level variability regarding trend strength and direction was abundant between neighboring parcels throughout most parts of the GAP (Figure S3, Figure S4).

Discussion

We characterized the spatio-temporal evolution of dry season irrigation in Turkey´s largest irrigation scheme by analyzing Landsat time series across 29 years. Our findings document the transformation of a rainfed agro-pastoralist system into an intensively used landscape through the expansion and intensification of irrigated agriculture. This drastic change was accompanied by a plethora of social, ecological, and economic externalities (Bilgen, 2018b; Bilgili et al., 2018; Özerol & Bressers, 2017). Excessive water consumption and soil salinization caused by area-based water pricing schemes, the absence of water use monitoring, low water-use efficiency, and water-intensive cropping patterns constitute the core challenges in the GAP region. Here we seek to contextualize our findings in light of these issues and outline opportunities to inform land management in the GAP region, or similar arid to semi-arid irrigation systems.

Water pricing in Turkey is based on the irrigated land area and crop type and does not impose volumetric restrictions on water use (Cakmak, 2010). Economic incentives to switch to water-saving methods are lacking, since the quantity of water used at the farm level is neither monitored nor incorporated into the irrigation fee. As a consequence, irrigation water use has been excessive and, combined with insufficient drainage, drastically raised the extent of saline lands in the GAP region (Bilgili et al., 2018; Kendirli et al., 2005). Our maps provide opportunities to assess cropland use history over three decades at 30 m spatial resolution and can thus serve as a spatially detailed indicator for soil salinization risk. For instance, our maps document that Şanlıurfa´s Harran plain has been used since the onset of the GAP project with rising intensity. The risk for environmental degradation is likely aggravated in this particularly dry region, and many studies already documented increasing soil salinity due to excessive irrigation (Altinbilek & Tortajada, 2012; Bahçeci & Nacar, 2009; Bilgili et al., 2018; Çullu, 2003).

Low water use efficiency stems from high rates of evaporation, seepage, and inefficient irrigation techniques, which further increase pressure on water resources in the GAP region (Cakmak et al., 2004; Unver, 1997; Yazar et al., 2002). The majority of the irrigation canals are open, with few subsurface piped systems (Özerol & Bressers, 2017). On-farm irrigation is primarily based on flood and furrow irrigation. Some farmers installed drip and sprinkle systems with subsidized credit from the Ministry of Agriculture after 2005 (Topcu et al., 2019). The persistence of inefficient irrigation techniques has been related to the regional land ownership structure. Approximately 40% of the farmers in the GAP region are landless, tenants, or smallholders with only a few hectares of land (Miyata & Fujii, 2007) who are risk-averse, lack collaterals to access credits, and rarely undertake costly investments into irrigation infrastructure (Demirdöğen et al., 2016; Topcu et al., 2019). Improving water use efficiency accordingly requires policies that incentivize the required investments for landowners, landless tenants, and smallholders (Özerol & Bressers, 2017).

The choice of crops determines water consumption and optimized cropping patterns are needed to reduce future water demand. Agricultural support payments are effectively controlling the crop choice in the GAP region (Demirdöğen et al., 2016; Özerol & Bressers, 2017). Subsidies on inputs (fertilizer, pesticides, fuel, irrigation fees, seeds) and output (crop-specific support payments), and the growing domestic textile sector explain the drastic expansion of cotton production (Solakoglu et al., 2013). Before the irrigation expansion, cotton cultivation covered less than 3% of Şanlıurfa and Mardin (Beaumont, 1996), and was also foreseen to occupy only a small share of the newly irrigated croplands (Özdoğan et al., 2006). In 2018, however, cotton was the major dry season crop in the GAP region and covered 3,100 km^2 or 54% of the dry season cropped area (USDA, 2018).

The estimation of crop water requirements over time and space can benefit from integrating annual maps of dry season crops with province-level crop production statistics and climate datasets.

Such information is particularly useful in the GAP region given the lack of spatially and temporally detailed data on water consumption. Moreover, such data can inform the spatial optimization of cropping patterns that aim at reduced water consumption (Davis et al., 2017). Given that climate change will likely elevate crop-water requirements in the Mediterranean (e.g., by 8% to 18% for cotton; Fader et al., 2016), such assessments allow to better explore the option space in future crop production (Fader et al., 2016; Malek et al., 2018).

We mapped the distribution of dry season cropping wall-to-wall for the GAP region over 29 years on an annual basis, which amends previous assessments of dry season crop expansion based on remote sensing (Özdoğan et al., 2006). The maps revealed an average expansion rate of 170 km^2 per year. Notably, 75% or more of the recent annual expansion and the majority of intensification occurred in only two provinces: Şanlıurfa and Mardin (Figure 5). This highlights the relevance of Şanlıurfa and Mardin in terms of production and as potential hotspots of future environmental degradation. Both provinces should hence be considered priority targets for agro-environmental policies targeting the protection of land and water resources. The estimates for the frequency of dry season cropping provide useful information in this regard, for instance, in assessing the compliance to new rules in agricultural support payments, which reject payments to farmers not rotating crops regularly (USDA, 2020). Dry season crops were cultivated on average every second year, but 10% of the croplands experienced dry season cropping in nine out of ten years since the first cultivation, for instance, in the Harran plain.

Contradicting policy paradigms of subsidizing water-saving techniques in parallel to supporting water-intensive crops and promoting cropland expansion in hydroclimatically unsuitable regions are apparent in the GAP region and other parts of the Mediterranean (Molle & Tanouti, 2017). Failure to improve the efficiency and management of irrigated systems in the Mediterranean under climate change will increase water scarcity, lead to the contraction of irrigated agriculture (Fader et al., 2016; Malek & Verburg, 2018), and foster further water-related conflicts across borders (Harris, 2002; Schillinger et al., 2020).

Our method for mapping dry season cropping annually for three decades relied on Landsat-based spectral-temporal metrics as a means for temporally consistent cropland mapping (Deines et al., 2017; Schmidt et al., 2016). Limited availability of reference data is a key constraint for mapping land cover time series in agricultural regions (Bégué et al., 2018). Here, we demonstrated that temporally consistent land use maps can be produced with training data from a single year. Transferring classification models through time and space requires that the image effects unrelated to land cover are minimized (Woodcock et al., 2001). The results of our independent validation speak in favor of the temporal consistency of spectral-temporal metrics. However, the accuracies of the dry season crop class were less stable in the early study period (e.g., 1995) and selected recent years (e.g., 2007 to 2009). Classification errors may be related to annual variations in the temporal distribution of Landsat observations, variations in temperature and precipitation that altered crop calendars, or combinations thereof. While a detailed investigation is beyond the scope of this study, further research can help to systematically isolate the sensitivity of spectral-temporal metrics towards these factors to further narrow down the sources of uncertainty. Our regional area estimates, however, are unbiased as they are based on a probability sampling design and stratified estimation (Olofsson et al., 2014; Stehman, 2014).

Conclusions

Assessing the dynamics of irrigated areas is essential to inform land and water resource management. We used a 29-year time series of Landsat imagery to quantify the expansion, cropping frequency, and changes thereof for irrigated dry season cultivation in Turkey´s largest irrigation scheme. The combination of Landsat-derived spectral-temporal metrics and a non-parametric classification algorithm yielded a robust long-term characterization of the regional cropping system at 30 m spatial and annual temporal resolution. The need for extensive reference datasets on irrigation status could be circumvented in the GAP region as dry season cultivation is fully based on irrigation and the spectral information contained in spectral-temporal metrics and composites facilitated the generation of accurate training and validation datasets. The approach thus offers potential for deriving long-term indicators of dry season cultivation in other semi-arid or arid irrigation systems.

Our maps revealed a six-fold expansion of dry season crops since 1990. Fields were on average cultivated every second dry season, with tendencies of intensification in 40% of the cropland. The agroecological conditions of the GAP region, coupled with low water use efficiency, area-based water pricing, and support payments favoring water-intensive crops, inflict excessive water consumption. Trade-offs between the envisioned expansion and intensification of irrigated cropland should be carefully evaluated to avoid future water shortages and land degradation. The long-term land use intensity indicators presented here can be combined with data on local biophysical conditions (precipitation, drought indices, soil quality), land management (e.g., irrigation technique, crop rotations, governance in water user associations), agricultural policies (e.g., crop-specific subsidies, rotation rules), market developments (e.g., variations in commodity prices), and production output (e.g., crop yield or market value) to assess key determinants of water demand and land use intensity, as well as their implications on the regional water resource base and downstream water users.

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Disclosure statement

No potential conflict of interest was reported by the authors.

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References

Altinbilek, D., & Tortajada, C. (2012). The Atatürk dam in the context of the southeastern Anatolia (GAP) project. In C. Tortajada, D. Altinbilek, & A.K. Biswas (Eds.), *Water resources development and management. impacts of large dams: A global Assessment* (pp. 171–199). Springer.

Ambika, A.K., Wardlow, B., & Mishra, V. (2016). Remotely sensed high resolution irrigated area mapping in India for 2000 to 2015. *Scientific Data*, *3(1)*, 160118. https://doi.org/10.1038/sdata.2016.118

Bahçeci, İ., & Nacar, A.S. (2009). Subsurface drainage and salt leaching in irrigated land in south-east Turkey. *Irrigation and Drainage*, *58*(3), 346–356. https://doi.org/10.1002/ird.400

Beaumont, P. (1996). Agricultural and environmental changes in the upper Euphrates catchment of Turkey and Syria and their political and economic implications. *Applied Geography*, *16*(2), 137–157. https://doi.org/10.1016/0143-6228(95)00033-X

Bégué, A., Arvor, D., Bellon, B., Betbeder, J., Abelleyra, D.D., Ferraz, P.D., Lebourgeois, R., Lelong, V., Simões, C., & Verón, R. (2018). Remote sensing and cropping practices: A review. *Remote Sensing*, *10*(2), 1–32. https://doi.org/10.3390/rs10010099

Bilgen, A. (2018a). The southeastern Anatolia project (GAP) in Turkey: An alternative perspective on the major rationales of GAP. *Journal of Balkan and near Eastern Studies*, *21*(5), 1–21. https://doi.org/10.1080/19448953.2018.1506287

Bilgen, A. (2018b). The southeastern Anatolia Project (GAP) revisited: The evolution of GAP over forty years. *New Perspectives on Turkey*, *58(1)*, 125–154. https://doi.org/10.1017/npt.2018.8

Bilgili, A.V., Yeşilnacar, İ., Akihiko, K., Nagano, T., Aydemir, A., Hızlı, H.S., & Bilgili, A. (2018). Post-irrigation degradation of land and environmental resources in the Harran plain, southeastern Turkey. *Environmental Monitoring and Assessment*, *190*(11), 660. https://doi.org/10.1007/s10661-018-7019-2

Breiman, L. (2001). Random forests. *Machine Learning*, *45*(1), 5–32. https://doi.org/10.1023/A:1010933404324

Cakmak, B., Beyribey, M., Yildirim, Y.E., & Kodal, S. (2004). Benchmarking performance of irrigation schemes: A case study from Turkey. *Irrigation and Drainage*, *53*(2), 155–163. https://doi.org/10.1002/ird.130

Cakmak, E.H. (2010). *Agricultural water pricing in Turkey: Economic co-operation and development. Sustainable management of water resources in agriculture*. OECD. https://doi.org/10.1787/787034266022

Cetin, M. (2020). Agricultural water use. In N.B. Harmancioglu & D. Altinbilek (Eds.), *Water resources of Turkey* (pp. pp. 257–302). Springer International Publishing. https://doi.org/10.1007/978-3-030-11729-0_9

Chen, Y., Lu, D., Luo, L., Pokhrel, Y., Deb, K., Huang, J., & Ran, Y. (2018). Detecting irrigation extent, frequency, and timing in a heterogeneous arid agricultural region using MODIS time series, Landsat imagery, and ancillary data. *Remote Sensing of Environment*, *204*(204), 197–211. https://doi.org/10.1016/j.rse.2017.10.030

Cochran, W.G. (1977). *Sampling Techniques*.3d ed Wiley

Çullu, M.A. (2003). Estimation of the effect of soil salinity on crop yield using remote sensing and geographic information system. *Turk J Agric For*, *27(1)*, 23–28. https://journals.tubitak.gov.tr/agriculture/issues/tar-03-27-1/tar-27-1-4-0209-13.pdf

Daccache, A., Ciurana, J.S., Rodriguez Diaz, J.A., & Knox, J.W. (2014). Water and energy footprint of irrigated agriculture in the Mediterranean region. *Environmental Research Letters*, *9*(12), 124014. https://doi.org/10.1088/1748-9326/9/12/124014

Dara, A., Baumann, M., Freitag, M., Hölzel, N., Hostert, P., Kamp, J., Müller, D., Prishchepov, A.V., & Kuemmerle, T. (2020). Annual Landsat time series reveal post-soviet changes in grazing pressure. *Remote Sensing of Environment*, *239(1)*, 111667. https://doi.org/10.1016/j.rse.2020.111667

Davis, K.F., Rulli, M.C., Seveso, A., & D'Odorico, P. (2017). Increased food production and reduced water use through optimized crop distribution. *Nature Geoscience*, *10*(12), 919–924. https://doi.org/10.1038/s41561-017-0004-5

Deines, J.M., Kendall, A.D., Crowley, M.A., Rapp, J., Cardille, J.A., & Hyndman, D.W. (2019). Mapping three decades of annual irrigation across the US high plains aquifer using Landsat and Google Earth Engine. *Remote Sensing of Environment*, *233(1)*, 111400. https://doi.org/10.1016/j.rse.2019.111400

Deines, J.M., Kendall, A.D., & Hyndman, D.W. (2017). Annual irrigation dynamics in the U.S. Northern high plains derived from Landsat satellite data. *Geophysical Research Letters*, *44*(18), 9350–9360. https://doi.org/10.1002/2017GL074071

Demirdöğen, A., Olhan, E., & Chavas, J.-P. (2016). Food vs. fiber: An analysis of agricultural support policy in Turkey. *Food Policy*, *61(1)*, 1–8. https://doi.org/10.1016/j.foodpol.2015.12.013

Dong, J., Metternicht, G., Hostert, P., Fensholt, R., & Chowdhury, R.R. (2019). Remote sensing and geospatial technologies in support of a normative land system science: Status and prospects. *Current Opinion in Environmental Sustainability*, *38(1)*, 44–52. https://doi.org/10.1016/j.cosust.2019.05.003

Erb, K.-H., Haberl, H., Jepsen, M.R., Kuemmerle, T., Lindner, M., Muller, D., Verburg, P.H., & Reenberg, A. (2013). A conceptual framework for analysing and measuring land-use intensity. *Current Opinion in Environmental Sustainability*, *5*(5), 464–470. https://doi.org/10.1016/j.cosust.2013.07.010

Ertek, A., & Yilmaz, H. (2014). The agricultural perspective on water conservation in Turkey. *Agricultural Water Management*, *143(1)*, 151–158. https://doi.org/10.1016/j.agwat.2014.07.009

Fader, M., Shi, S., Bloh, W., Von, Bondeau, A., & Cramer, W. (2016). Mediterranean irrigation under climate change: More efficient irrigation needed to compensate for increases in irrigation water requirements. *Hydrology and Earth System Sciences*, *20*(2), 953–973. https://doi.org/10.5194/hess-20-953-2016

Flood, N. (2013). Seasonal composite Landsat TM/ETM+ images using the medoid (a multi-dimensional median). *Remote Sensing*, *5*(12), 6481–6500. https://doi.org/10.3390/rs5126481

Foley, J.A., Ramankutty, N., Brauman, K.A., Cassidy, E.S., Gerber, J.S., Johnston, M., Mueller, N.D., O'Connell, C., Ray, D.K., West, P.C., Balzer, C., Bennett, E.M., Carpenter, S.R., Hill, J., Monfreda, C., Polasky, S., Rockström, J., Sheehan, J., Siebert, S., & Zaks, D.P.M. (2011). Solutions for a cultivated planet. *Nature*, *478*(7369), 337–342. https://doi.org/10.1038/nature10452

Frantz, D., Roder, A., Stellmes, M., & Hill, J. (2016). An operational radiometric Landsat preprocessing framework for large-area time series applications. *IEEE Transactions on Geoscience and Remote Sensing*, *54*(7), 3928–3943. https://doi.org/10.1109/TGRS.2016.2530856

GAP. (2017). *Latest state in GAP*. http://www.gap.gov.tr/en/latest-state-in-gap-page-47.html

Gerten, D., Heinke, J., Hoff, H., Biemans, H., Fader, M., & Waha, K. (2011). Global water availability and requirements for future food production. *Journal of HYDROMETEOROLOGY*, *12*(5), 885–899. https://doi.org/10.1175/2011JHM1328.1

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment*, *202(1)*, 18–27. https://doi.org/10.1016/j.rse.2017.06.031

Griffiths, P., van der Linden, S., Kuemmerle, T., & Hostert, P. (2013). A pixel-based Landsat compositing algorithm for large area land cover mapping. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *6*(5), 2088–2101. https://doi.org/10.1109/JSTARS.2012.2228167

Harris, L.M. (2002). Water and conflict geographies of the southeastern anatolia project. *Society & Natural Resources*, *15* (8), 743–759. https://doi.org/10.1080/08941920290069326

Hommes, L., Boelens, R., & Maat, H. (2016). Contested hydrosocial territories and disputed water governance: Struggles and competing claims over the Ilisu Dam development in southeastern Turkey. *Geoforum*, *71(1)*, 9–20. https://doi.org/10.1016/j.geoforum.2016.02.015

Jägermeyr, J., Gerten, D., Heinke, J., Schaphoff, S., Kummu, M., & Lucht, W. (2015). Water savings potentials of irrigation systems: Global simulation of processes and linkages. *Hydrology and Earth System Sciences*, *19*(7), 3073–3091. https://doi.org/10.5194/hess-19-3073-2015

Jakimow, B., van der Linden, S., Thiel, F., Frantz, D., & Hostert, P. (2020). Visualizing and labeling dense multi-sensor earth observation time series: The EO time series viewer. *Environmental Modelling and Software*, *125(1)*, 104631. https://doi.org/10.1016/j.envsoft.2020.104631

Kankal, M., Nacar, S., & Uzlu, E. (2016). Status of hydropower and water resources in the Southeastern Anatolia project (GAP) of Turkey. *Energy Reports*, *2(1)*, 123–128. https://doi.org/10.1016/j.egyr.2016.05.003

Kendirli, B., Cakmak, B., & Ucar, Y. (2005). Salinity in the southeastern Anatolia project (GAP), Turkey: Issues and options. *Irrigation and Drainage*, *54*(1), 115–122. https://doi.org/10.1002/ird.157

Kennedy, R., Yang, Z., Gorelick, N., Braaten, J., Cavalcante, L., Cohen, W., & Healey, S. (2018). Implementation of the LandTrendr Algorithm on Google Earth Engine. *Remote Sensing, 10*(5), 691. https://doi.org/10.3390/rs10050691

Löw, F., Prishchepov, A., Waldner, F., Dubovyk, O., Akramkhanov, A., Biradar, C., & Lamers, J. (2018). Mapping cropland abandonment in the aral sea basin with MODIS time series. *Remote Sensing*, *10*(2), 159. https://doi.org/10.3390/rs10020159

Malek, Ž., & Verburg, P.H. (2018). Adaptation of land management in the Mediterranean under scenarios of irrigation water use and availability. *Mitigation and Adaptation Strategies for Global Change*, *23*(6), 821–837. https://doi.org/10.1007/s11027-017-9761-0

Malek, Ž., Verburg, P.H., Geijzendorffer, R., Bondeau, I., & Cramer, W. (2018). Global change effects on land management in the Mediterranean region. *Global Environmental Change*, *50(1)*, 238–254. https://doi.org/10.1016/j.gloenvcha.2018.04.007

Mekonnen, M.M., & Hoekstra, A.Y. (2016). Four billion people facing severe water scarcity. *Science Advances*, *2*(2), e1500323. https://doi.org/10.1126/sciadv.1500323

Metin Sezen, S., & Yazar, A. (2006). Wheat yield response to line-source sprinkler irrigation in the arid Southeast Anatolia region of Turkey. *Agricultural Water Management*, *81*(1–2), 59–76. https://doi.org/10.1016/j.agwat.2005.04.011

Miyata, S., & Fujii, T. (2007). Examining the socioeconomic impacts of irrigation in the Southeast Anatolia region of Turkey. *Agricultural Water Management*, *88*(1–3), 247–252. https://doi.org/10.1016/j.agwat.2006.11.001

Molle, F., & Tanouti, O. (2017). Squaring the circle: Agricultural intensification vs. water conservation in Morocco. *Agricultural Water Management*, *192(1)*, 170–179. https://doi.org/10.1016/j.agwat.2017.07.009

Olofsson, P., Foody, G.M., Herold, M., Stehman, S.V., Woodcock, C.E., & Wulder, M.A. (2014). Good practices for estimating area and assessing accuracy of land change. *Remote Sensing of Environment*, *148(1)*, 42–57. https://doi.org/10.1016/j.rse.2014.02.015

Özdoğan, M., Woodcock, C.E., Salvucci, G.D., & Demir, H. (2006). Changes in summer irrigated crop area and water use in southeastern Turkey from 1993 to 2002: Implications for current and future water resources. *Water Resources Management*, *20*(3), 467–488. https://doi.org/10.1007/s11269-006-3087-0

Özdoğan, M., Yang, Y., Allez, G., & Cervantes, C. (2010). Remote sensing of irrigated agriculture: Opportunities and challenges. *Remote Sensing*, *2*(9), 2274–2304. https://doi.org/10.3390/rs2092274

Özerol, G., & Bressers, H. (2017). How do farmers align with the agri-environmental changes in irrigated agriculture? A case study from the harran plain, Turkey. *Irrigation and Drainage*, *66*(1), 45–59. https://doi.org/10.1002/ird.2064

Phalke, A.R., & Özdoğan, M. (2018). Large area cropland extent mapping with Landsat data and a generalized classifier. *Remote Sensing of Environment*, *219(1)*, 180–195. https://doi.org/10.1016/j.rse.2018.09.025

Porkka, M., Gerten, D., Schaphoff, S., Siebert, S., & Kummu, M. (2016). Causes and trends of water scarcity in food production. *Environmental Research Letters*, *11*(1), 15001. https://doi.org/10.1088/1748-9326/11/1/015001

Ray, D.K., & Foley, J.A. (2013). Increasing global crop harvest frequency: Recent trends and future directions. *Environmental Research Letters*, *8*(4), 44041. https://doi.org/10.1088/1748-9326/8/4/044041

Rosa, L., Rulli, M.C., Davis, K.F., Chiarelli, D.D., Passera, C., & D'Odorico, P. (2018). Closing the yield gap while ensuring water sustainability. *Environmental Research Letters*, *13*(10), 104002. https://doi.org/10.1088/1748-9326/aadeef

Rufin, P., Frantz, D., Ernst, S., Rabe, A., Griffiths, P., Özdoğan, M., & Hostert, P. (2019). Mapping cropping practices on a national scale using intra-annual landsat time series binning. *Remote Sensing*, *11*(3), 232. https://doi.org/10.3390/rs11030232

Rufin, P., Levers, C., Baumann, M., Jägermeyr, J., Krueger, T., Kuemmerle, T., & Hostert, P. (2018). Global-scale patterns and determinants of cropping frequency in irrigation dam command areas. *Global Environmental Change*, *50(1)*, 110–122. https://doi.org/10.1016/j.gloenvcha.2018.02.011

Schillinger, J., Özerol, G., Güven-Griemert, Ş., & Heldeweg, M. (2020). Water in war: Understanding the impacts of armed conflict on water resources and their management. *Wiley Interdisciplinary Reviews: Water*, *7*(6), 31. https://doi.org/10.1002/wat2.1480

Schmidt, M., Pringle, M., Devadas, R., Denham, R., & Tindall, D. (2016). A framework for large-area mapping of past and present cropping activity using seasonal landsat images and time series metrics. *Remote Sensing*, *8*(4), 312. https://doi.org/10.3390/rs8040312

Singh, A. (2016). Evaluating the effect of different management policies on the long-term sustainability of irrigated agriculture. *Land Use Policy*, *54(1)*, 499–507. https://doi.org/10.1016/j.landusepol.2016.03.012

Solakoglu, E.G., Er, S., & Solakoglu, M.N. (2013). Technical efficiency in cotton production: The role of premium payments in Turkey. *Transition Studies Review*, *20*(3), 285–294. https://doi.org/10.1007/s11300-013-0286-2

Stehman, S.V. (2014). Estimating area and map accuracy for stratified random sampling when the strata are different from the map classes. *International Journal of Remote Sensing*, *35*(13), 4923–4939. https://doi.org/10.1080/01431161.2014.930207

Topcu, S., Kibaroglu, A., & Kadirbeyoglu, Z. (2019). Turkey. In F. Molle, C. Sanchis-Ibor, & L. Avellà-Reus (Eds.), *Irrigation in the Mediterranean: Technologies, institutions and policies* (pp. pp. 185–212). Springer International Publishing. https://doi.org/10.1007/978-3-030-03698-0_7

UNEP. (2004). *Analyzing environmental trends using satellite data: Selected cases. Environment change analysis series*. United Nations Environment Programme, Division of Early Warning and Assessment.

Unver, I.H.O. (1997). South-eastern Anatolia integrated development project (GAP), Turkey: An overview of issues of sustainability. *International Journal of Water Resources Development*, *13*(2), 187–208. https://doi.org/10.1080/07900629749827

USDA. (2018). *Turkey cotton and products annual* (GAIN Report TR8009). https://gain.fas.usda.gov/Recent%20GAIN%20Publications/Cotton%20and%20Products%20Annual_Ankara_Turkey_3-23-2018.pdf

USDA. (2020). *Turkey cotton and products annual* (GAIN Report TU2020-0005). https://apps.fas.usda.gov/newgainapi/api/Report/DownloadReportByFileName?fileName=Cotton%20and%20Products%20Annual_Ankara_Turkey_04-01–2020

Waldner, F., Hansen, M.C., Potapov, P.V., Löw, F., Newby, T., Ferreira, S., & Defourny, P. (2017). National-scale cropland mapping based on spectral-temporal features and outdated land cover information. *PLoS ONE*, *12*(8), e0181911. https://doi.org/10.1371/journal.pone.0181911

Woodcock, C.E., Macomber, S.A., Pax-Lenney, M., & Cohen, W.B. (2001). Monitoring large areas for forest change using Landsat: Generalization across space, time and Landsat sensors. *Remote Sensing of Environment*, *78*(1–2), 194–203. https://doi.org/10.1016/S0034-4257(01)00259-0

Wulder, M.A., Coops, N.C., Roy, D.P., White, J.C., & Hermosilla, T. (2018). Land cover 2.0. *International Journal of Remote Sensing*, *39*(12), 4254–4284. https://doi.org/10.1080/01431161.2018.1452075

Wulder, M.A., Loveland, T.R., Roy, D.P., Crawford, C.J., Masek, J.G., Woodcock, C.E., Allen, R.G., Anderson, M.C., Belward, A. S., Cohen, W.B., Dwyer, J., Erb, A., Gao, F., Griffiths, P., Helder, D., Hermosilla, T., Hipple, J.D., Hostert, P., Hughes, M.J., Johnson, D.M., … Zhu, Z. (2019). Current status of Landsat program, science, and applications. *Remote Sensing of Environment*, *225(1)*, 127–147. https://doi.org/10.1016/j.rse.2019.02.015

Wulder, M.A., Masek, J.G., Cohen, W.B., Loveland, T.R., & Woodcock, C.E. (2012). Opening the archive: How free data has enabled the science and monitoring promise of landsat. *Remote Sensing of Environment*, *122(1)*, 2–10. https://doi.org/10.1016/j.rse.2012.01.010

Yazar, A., Metin Sezen, S., & Gencel, B. (2002). Drip irrigation of corn in the southeast anatolia project (GAP) Area in Turkey. *Irrigation and Drainage*, *51*(4), 293–300. https://doi.org/10.1002/ird.63

Zhu, Z., Wang, S., & Woodcock, C.E. (2015). Improvement and expansion of the Fmask algorithm: Cloud, cloud shadow, and snow detection for Landsats 4–7, 8, and Sentinel 2 images. *Remote Sensing of Environment*, *159(1)*, 269–277. https://doi.org/10.1016/j.rse.2014.12.014

Zhu, Z., Wulder, M.A., Roy, D.P., Woodcock, C.E., Hansen, M.C., Radeloff, V.C., Healey, S.P., Schaaf, C., Hostert, P., Strobl, P., Pekel, J.-F., Lymburner, L., Pahlevan, N., & Scambos, T.A. (2019). Benefits of the free and open Landsat data policy. *Remote Sensing of Environment*, *224(1)*, 382–385. https://doi.org/10.1016/j.rse.2019.02.016