SUPPLIMENTARY MATERIAL

A GIS-based approach to inform agriculture-water-energy nexus planning in the North Western Sahara Aquifer System (NWSAS)

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Methods

The section is divided into four consecutive sub-sections that build on each other. starting by GIS data collection; then moving to cropland calibration method to develop a GIS map of the irrigated cropland layer; then estimating the irrigation water requirements; which will then feed into the estimation of the electricity requirement for pumping. Finally, the last sub-section describes the method implemented to find the least cost electricity supply option in each location. Figure S1 represents a schematic overview of the approach.

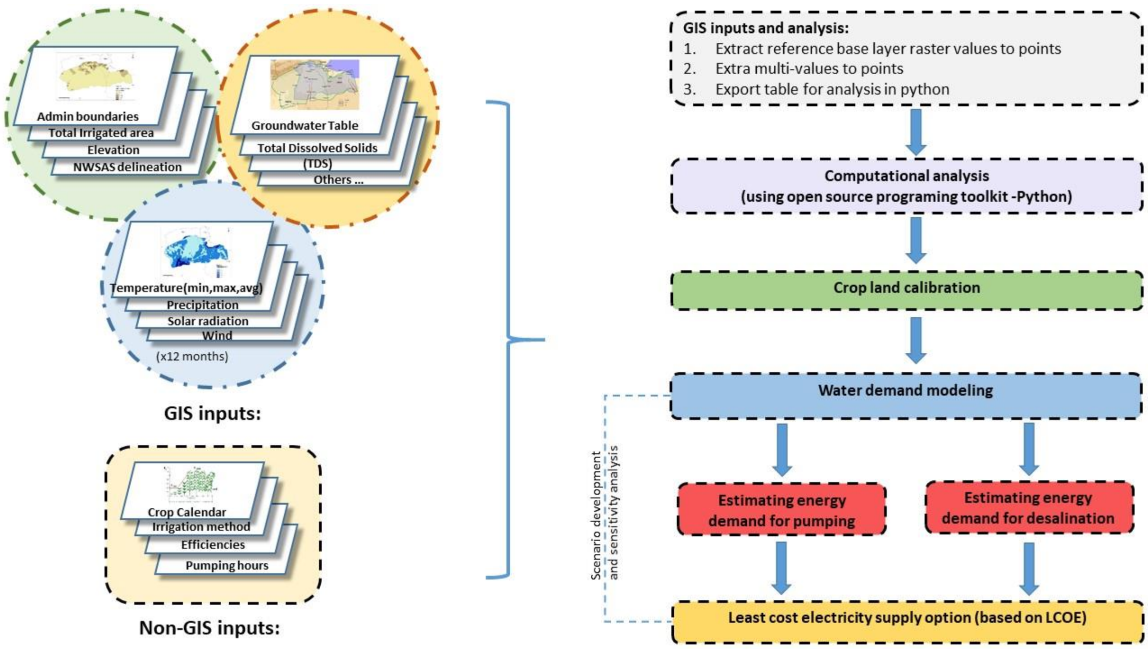

Figure S1: Schematic representation of the methodology used for estimating the electricity demand for groundwater irrigation in the NWSAS.

1.1 GIS data Collection

The first step of the analysis consisted of data rendering and cleaning. Climatic datasets such as temperature, wind speed, solar irradiation and precipitation were collected on a monthly basis. Other biophysical characteristics such as elevation, water table and ground properties were collected on an aggregated – annual – basis. All the collected layers were spatially processed and projected to a 1kmX1km resolution map using World Mercator as the projection system [1] which is consistent with the obtained datasets. Table S1 provides a more detailed description of the datasets characteristics.

Table S1. Summary table of the GIS layers used in this analysis

#	Dataset	Type	Resolution	Spatial scope	Source
1	Administrative boundaries	Vector polygon	-	Administrative levels	[2]
2	Elevation (m)	Raster	1 km × 1 km	Water/Energy demand	[3]
3	Cropland area (ha)	Raster	20 m x 20 m	Water/Energy demand	[4]
4	Irrigated harvested area (ha)	Raster	20 m x 20 m		[4]
5	Minimum monthly temperature (°C)	Raster	1 km × 1 km	Water demand	[2]
6	Maximum monthly temperature (°C)	Raster	1 km × 1 km	Water demand	[2]
7	Average monthly temperature (°C)	Raster	1 km × 1 km	Water demand	[2]
8	Monthly solar radiation (kJ m^{-2} day^{-1})	Raster	1 km × 1 km	Water demand/Energy Supply	[2]
9	Monthly wind speed (m s^{-1})	Raster	1 km × 1 km	Water demand	[2]
10	Monthly precipitation (mm)	Raster	1 km × 1 km	Water demand	[2]
11	Water table depth (m)	Raster	1 km × 1 km	Energy demand	[5]

Wind potential

GIS data of the monthly wind speeds at 1 km spatial resolution were obtained by the WorldClim [2] based on monthly data from 1970 – 2000. This data was geospatially processed to 12 layers each showing data for one month of the year for each grid cell in (m/sec) which was further processed into python and used to calculate the reference evapotranspiration and the LCOE as will be demonstrated in the following sections. Figure S2 shows the wind speed in the NWSAS region in April.

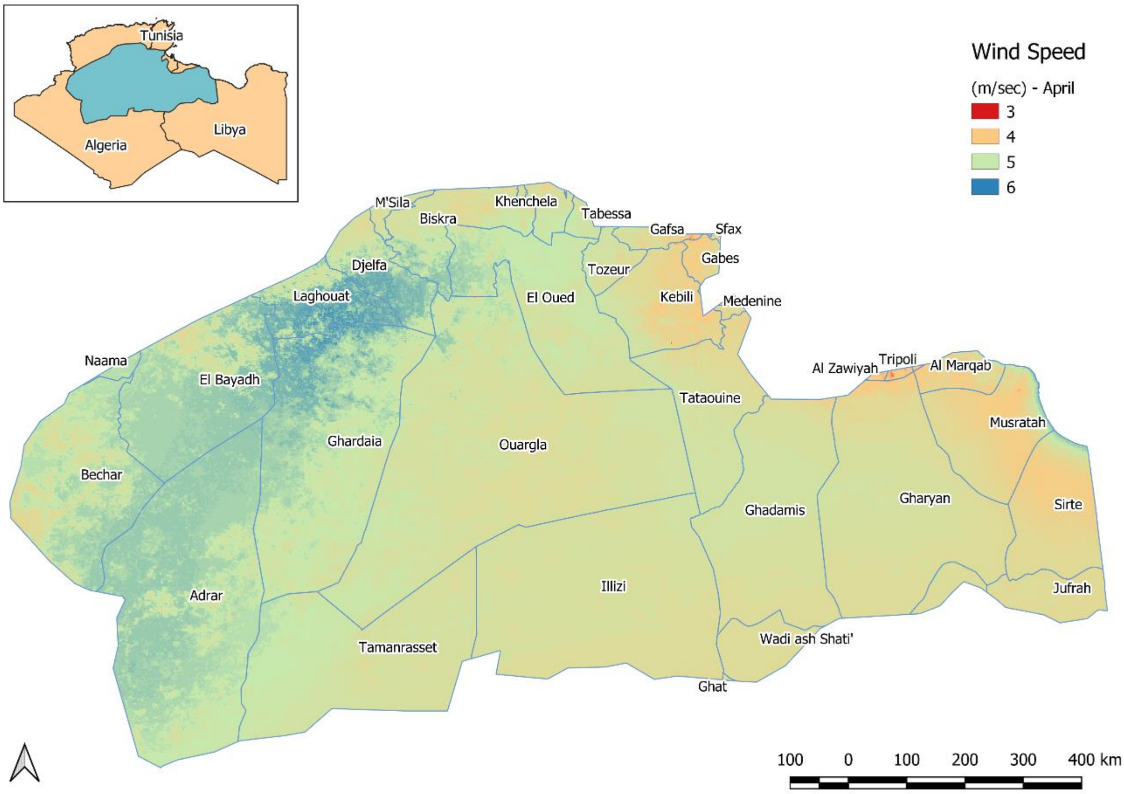

Figure S2. Wind speed in the NWSAS in (m/sec) for the month of April.

Solar energy potentials

The global solar data set was obtained from WorldClim [2]. This represents average monthly solar radiation in (kJ m-2 day-1) for 1970-2000 at 1 km resolution. The solar radiation data were further processed using standard geospatial analysis to convert it to 12 layers each showing data for one month of the year for each grid cell in (kWh m-2 month−1). This was used as an input parameter for the LCOE calculation of stand-alone solar PVs which is based on the radiation, the system costs and the electricity demand for irrigation. An illustration of the solar radiation map is shown in Figure S3.

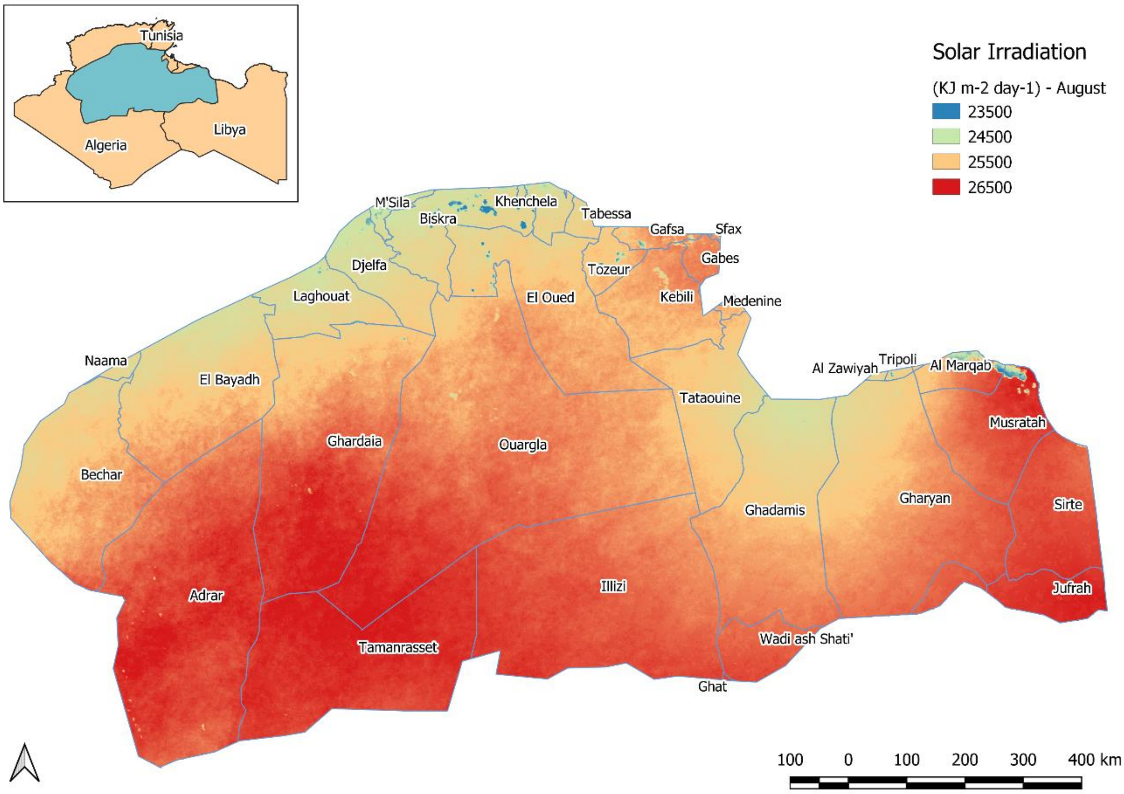

Figure S3. Solar radiation in NWSAS region in (KJ m-2 day-1) in August.

The following table shows the extracted values for monthly solar radiation in each province and the total annual radiation in (KWh/m2).

Table S2. Monthly and yearly solar radiation in (KWh/m2).

Province	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Annual sum
Adrar	123	150	184	212	223	232	233	219	192	157	127	114	2 166
Biskra	85	114	149	179	208	214	225	204	171	127	91	78	1 845
Djelfa	90	121	154	182	210	219	224	206	172	131	97	82	1 889
El Oued	92	124	155	183	211	215	229	212	175	133	100	85	1 915
Gabes	95	121	147	175	203	210	231	215	170	132	103	88	1 890
Ghadamis	103	129	155	177	205	207	225	208	169	136	110	95	1 918
Ghardaia	107	137	170	197	217	224	231	215	177	143	109	99	2 027
Gharyan	101	128	154	176	203	208	228	212	169	135	109	93	1 916
Illizi	121	148	176	196	212	215	229	217	184	155	123	112	2 090

Jufrah	115	142	165	177	205	212	230	219	178	144	123	105	2 016
Kebili	93	121	149	176	205	209	229	214	170	133	103	86	1 887
Khenchela	91	116	147	175	202	212	228	209	169	127	95	83	1 852
Laghouat	90	120	154	184	210	218	222	205	171	131	97	82	1 885
Musrata	90	121	146	173	202	209	225	208	162	127	102	82	1 847
Ouargla	103	134	166	193	214	218	232	214	179	141	108	95	1 997
Tamanrasset	127	153	186	211	221	226	233	220	192	160	129	116	2 173
Tataouine	100	126	151	176	206	208	227	211	169	134	107	92	1 906
Tebessa	91	118	149	175	205	212	229	210	170	129	98	84	1 870
Tozeur	92	119	148	174	204	209	227	210	169	130	100	86	1 869

Water table depth:

Data for water table depth were obtained from [5] which shows global observations of water table depth compiled from government archives and literature along with the use of a groundwater model, forced by modern climate, terrain, and sea level, to fill in data gaps and infer patterns. The resulting map shows simulated water table depth in (m) at 1 km resolution as illustrated in Figure S4. The average, minimum and max water table levels for each province were extracted from the dataset and show in Table S3. The depth to water table was used as input to calculate the energy requirement for pumping as will be shown later. It is worth mentioning that data from the GIS layer were validated with measurement data provided by OSS. However, both sources show different values compared to the maximum water depth of CT and CI reported in the literature.

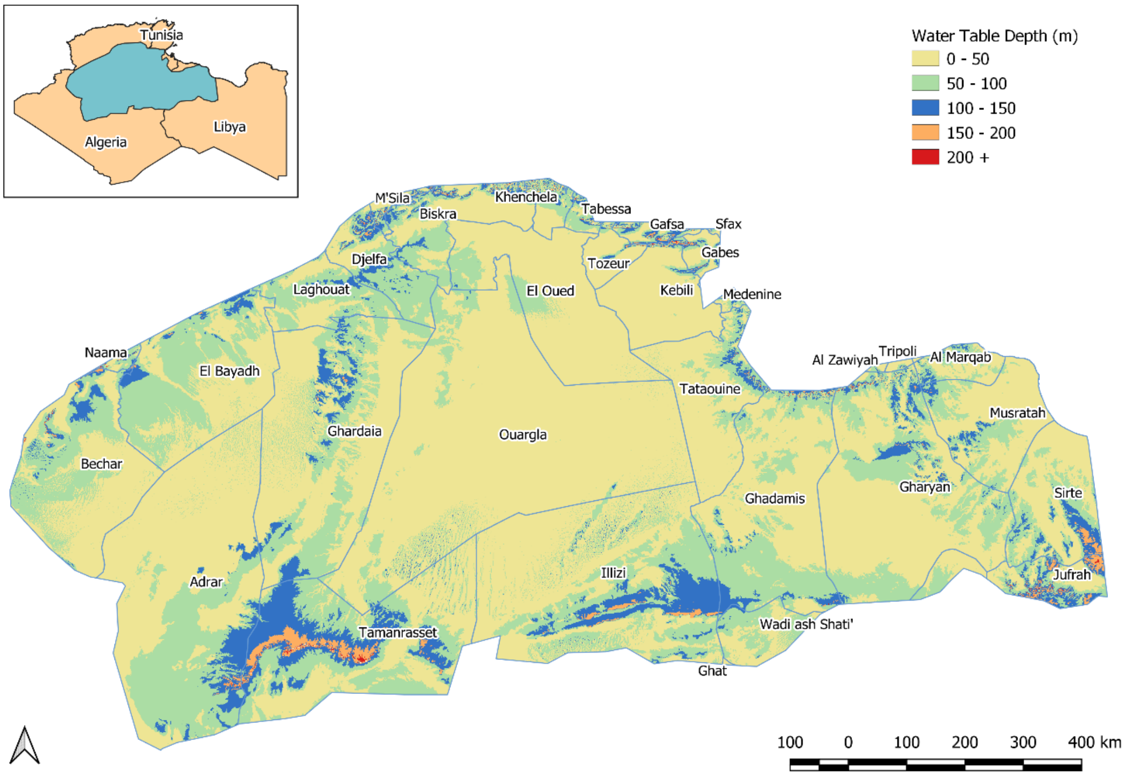

Figure S4. Water table depth in NWSAS region in (m).

Table S3. Summary of water table depth values for each province.

Country	Province	Ground water depth (m) (a)		
		avg	min	max
Algeria	Adrar	37	0	166
	Biskra	62	5	178
	Djelfa	44	0	180
	El Oued	35	0	81
	Ghardaia	44	0	158
	Illizi	66	0	161
	Khenchela	83	46	192
	Laghouat	12	0	77
	Ouargla	22	0	116
	Tamanrasset	72	0	226
	Tebessa	40	19	58
Libya	Ghadamis	87	0	235
	Gharyan	62	0	318
	Jufrah	57	0	252
	Musrata	27	0	130
Tunisia	Gabes	74	3	224
	Kebili	26	0	235
	Tataouine	79	0	208
	Tozeur	43	0	186

(a) Data extracted from map [5].

1.2 Cropland calibration

The cropland layer is a crucial component of this analysis. It provides a classification of land types and can be used as a proxy for identifying cultivated and/or irrigated area. There are several GIS land cover and cropland data options available [6] [7] [8]. The European Spatial Agency's (ESA) Climate Change Initiative (CCI) land cover S2 prototype for Africa dataset [4] provides a fine spatial resolution throughout the entire NWSAS region. Using ESA CCI, the total cropland area in the NWSAS was estimated at 860,000 ha. However, national statistics indicate only about 270,000 ha of irrigated land (using NWSAS groundwater) in the same region. Consultation with local stakeholders was performed in order to understand the sources of classification error in ESA CCI map and identify the parameters that increase the probability of cropland to be irrigated with NWSAS groundwater. This consultation process allowed for the development of a calibration methodology to eliminate the misclassification errors and identify croplands using groundwater, based on a Multi-Criteria Decision Analysis (MCDA)[1]. Four (potential) sources of misclassification in the ESA CCI were identified. They included sparse vegetation, rain-fed crops, irrigated crops using surface water and irrigated crops using water from external sources (in relation to NWSAS) such as nearby dams. Following an Analytical Hierarchy Process (AHP) [9] the decision criteria were ranked and weighted by local experts. The AHP process has been previously used for conducting suitability analysis of GIS-based problems, assisting the creation of land suitability for farming maps [10], [11], land slide susceptibility maps [12] and assessment of groundwater potential zones [13], proofing its effectiveness for GIS applications. Four decision criteria were selected to address different sources of misclassification, as presented in Table S4.

Table S4. Cropland calibration process decision criteria.

Decision criteria	Error description	Calibration process
Distance from rivers	Sparse vegetation that is very close to river beds is more probable of being misclassified as croplands. Croplands close to rivers have a higher probability of being irrigated by surface water.	Decrease the probability of data points that are close to rivers, of being cropland irrigated by NWSAS groundwater.
Cropland density	Very small crop fields and/or low crop density areas are less likely to be irrigated by groundwater (due to high pumping cost).	Decrease the probability of data points with low-density area, of being cropland irrigated by groundwater.
Distance to dams	Croplands located in proximity to dams are less likely to be irrigated by groundwater.	Decrease the probability of data points that are close to dams, of being cropland irrigated by groundwater.
Known irrigated areas	In some areas the presence of irrigated agriculture is certain. Data points within those areas are more probable to be irrigated, whereas data points outside those areas are more probable of being classified as sparse vegetation or rain-fed cropland.	Increase the probability of data points within known irrigated areas to be irrigated by groundwater. The global dataset of the irrigated area serviced by groundwater from AQUASTAT was used.

[1] Data obtained from Sahara and Sahel Observatory (OSS).

The selected decision criteria help at increasing or decreasing the confidence that some areas are irrigated through groundwater, meaning that a "correction factor" is applied to the map. In three cases is a "negative" factor (i.e. decrease probability) and in one case is "positive" (i.e. increase probability).

The aforementioned decision criteria were then ranked, making use of a pairwise comparison matrix, in order to compute weights that are then applied as "correction factors" to the ESA CCI map. Each criterion was ranked against every other in a scale ranging from 1 to 9 according to the fundamental ranking scale of the AHP method (see Table S5).

Table S5. Ranking system scale for pairwise comparisons (R. W. Saaty, 1987)

Importance ranking	Definition
1	Equal importance.
3	Moderate importance of one over another.
5	Strong importance of one over another.
7	Very strong importance of one over another.
9	Extreme importance of one over another.
2, 4, 6, 8	Intermediate values.
Reciprocals	If criteria i has a value A when compared to criteria j, then j will have the inverse value 1/A when compared to i.

Criteria weights were computed according to the AHP methodology, and the consistency of the matrix was reviewed by calculating a Coherence Ratio (CR). Such ratio indicates the level of consistency the decision-maker had when assigning the pairwise rankings for the criteria. In principle, a CR < 0.1 indicates a consistent matrix. The rankings, computed weights and CR value are presented in Table S6.

Table S6. Pairwise comparison matrix, weights and CR for the selected criteria.

	Distance from rivers	Cropland density	Distance to dams	Irrigated areas map	Computed weight
Distance from rivers	1	1/2	3	1/4	0.14
Cropland density	2	1	1/4	1/9	0.055
Distance to to dams	1/3	4	1	1/3	0.22
Irrigated areas map	4	9	3	1	0.57

Consistency Ratio (CR) = 0.0115

A Weighted Linear Combination (WLC) approach was used to compute a suitability map based on the weights obtained with the AHP method for each criterion [14]. For this, all decision criteria layers were normalized to a 0 to 1 scale, making use of the Python scikit-learn MinMax scaler [15]. The normalized layers were then multiplied in a per cell basis by their respective weights, and summed up to obtain an overall cropland suitability map according to.

$$Grid_{suitability\ map} = \sum (Grid_i \times weight_i)$$

Where; $Grid_i$ is criteria i and $weight_i$ is the corresponding weight.

The obtained suitability map consists of a GIS layer containing pixels ranging from 0 to 1, indicating the suitability of the area of having croplands irrigated by groundwater (see Figure S5).

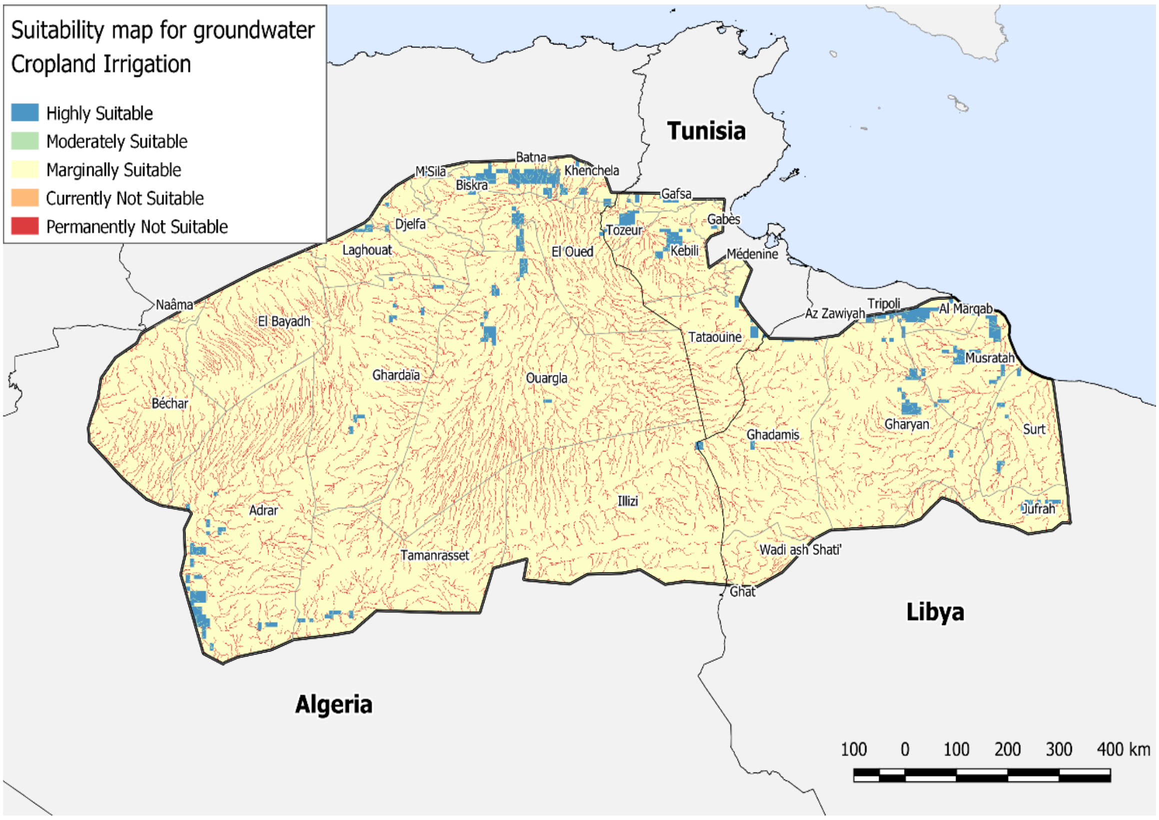

Figure S5. Map of suitable areas for cropland classification. Areas in red represent the most unsuitable ones for using groundwater for irrigation, as they are very close to surface resources, outside identified irrigated areas or in proximity to other water sources as dams.

Using ESA CCI and the suitability map (Figure S5) the cropland area[2] of each province was calibrated to match its national statistic, with a tolerance range of ±15% previously agreed with local stakeholders. For the provinces were the cropland area was lower than the national statistic and did not comply with the -15% tolerance, an additional layer from FROM-GLC version2 [16] global land cover was used. The new layer complements the ESA CCI layer, rising the cropland area to the tolerance range of ±15%.

1.3 Estimation of the irrigation water requirement

Estimation of the reference crop evapotranspiration (ETo)

There are more than 50 mathematical models are currently available to estimate ET_o, ranging from hydrologic or water balance models to analytical methods based on climate variables (primarily

[2] In GIS using zonal statistics, the cropland count represents the area.

temperature and radiation) and empirical estimates. The only factors affecting ET_o are climatic parameters, so ET_o can be computed from weather data without taking into account crop characteristics or soil factors. Several studies, however, have shown that the physically based Penman-Monteith formula (1965) [17], which considers both climatic factors and their interaction with surface vegetation characteristics, is the most accurate. Penman and Monteith combined the energy balance with the mass transfer method and derived multiple equations in order to compute the evaporation from an open water surface from standard climatological records of sunshine, temperature, humidity and wind speed. The FAO-56 Penman-Monteith method was adapted in 1990 by a consultation of FAO experts and researchers in collaboration with the International Commission for Irrigation and Drainage and the World Meteorological Organization [18]. This method overcomes shortcomings of the old Penman and Monteith equations and provides values more consistent with actual crop water use data worldwide. According to this method, ET_o is defined as the “evapotranspiration of a hypothetical reference crop with a height of 0.12 m, a surface aerodynamic resistance of 70 s m^{-1} and an albedo of 0.23, closely resembling an extensive surface of green grass of uniform height, actively growing, completely shading the ground and with adequate water” [18]. The formula that describes this is:

$$ETo = \frac{0.408\Delta\,(R_n - G) + \gamma\,\frac{900}{T + 273}\,u_2\,(e_s - e_a)}{\Delta + \gamma\,(1 + 0.34\,u_2)}$$

Where; ET_o is the reference evapotranspiration (mm day^{-1}), R_n is the net radiation at the crop surface (MJ m^{-2} day^{-1}), G is soil heat flux density (MJ m^{-2} day^{-1}), T is the mean daily air temperature at 2m height (°C), u_2 is the wind speed at 2m height (ms^{-1}), e_s is the saturation vapour pressure (kPa), e_a is the actual vapour pressure (kPa), e_s - e_a is the saturation vapour pressure deficit (kPa), Δ is the slope vapour pressure curve (kPa $°C^{-1}$) and γ the psychrometric constant (kPa $°C^{-1}$).

To be able to automate this calculation for a large region like the NWSAS, “Pyeto” Python library was used to calculate meteorological parameters from climate data [19]. Furthermore, Pyeto provides numerous functions for estimating missing meteorological data such as net outgoing longwave radiation, psychometric constant, soil heat flux, saturated vapour pressure, solar angles, daylight hours etc based on the methods described by Allen et al. (1998).

Crop evapotranspiration under standard conditions (ETc) and single crop coefficient (kc)

The crop evapotranspiration under standard conditions (ET_c) is the evapotranspiration from disease-free, well-fertilized crops, grown in large fields under optimum soil water conditions, and achieving full production under the given climatic conditions. The crop coefficient (kc) depends on the type of crop, the growth stage of the crop and the climate. The values are extracted from literature as shown in Table 2 in the main manuscript) based on crop coefficient curve (Figure S6) which incorporates distinct growing periods [20]:

1. The **initial stage** is the period from sowing or transplanting until the crop covers about 10% of the ground.
2. The crop **development stage** starts at the end of the initial stage and lasts until the full ground cover has been reached (ground cover 70-80%); it does not necessarily mean that the crop is at its maximum height.
3. The **mid-season stage** starts at the end of the crop development stage and lasts until maturity; it includes flowering and grain-setting.
4. The **late-season** stage lasts until the last day of the harvest and usually includes ripening.

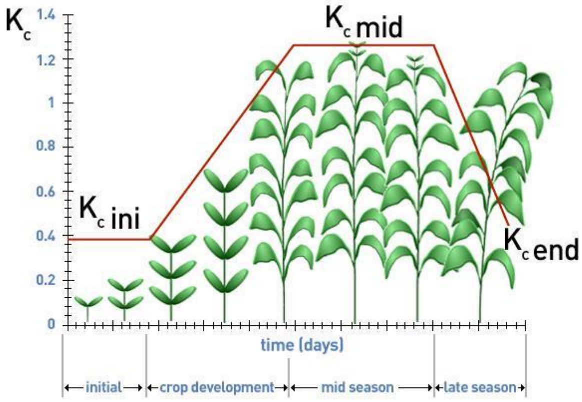

Figure S6. Variation in crop factor (Kc) in each growing season [18].

After extracting data for kc for each crop at each growing cycle, the ET_c is calculated from ET_o by simply multiplying with a crop-specific coefficient, k_c:

$$ET_c = ET_o * k_c$$

Modelling of water demand

The water supply of the irrigation scheme must be equal to the demand throughout all the growing stages of the crop(s) planted. The water requirements to meet demand depend on the crop water requirements (expressed by ET_c), climatic and land conditions, and the field application and distribution efficiencies.

Monthly crop water needs

To estimate the monthly aggregated crop water requirements (CWN_i), the outputs obtained in the previous steps, are used as primary inputs. Along with the monthly ET_c values, additional climatic and land variables are either calculated or introduced from the literature, allowing for a more inclusive and accurate parameterization and estimation of the actual crop water needs at a given location. There are several approaches taken in the literature, from simple water balance models to more complex hydrological analysis. The method followed in this study relies on a simplified, yet comprehensive, combination approach that takes into account mainly the effective rainfall (mm) and the crop water requirement. The leaching requirements (%) and the available water content in the root zone (mm) at a given point were assumed negligible in this arid climate. The following equation was used in this step [21]:

$$CWN_i = ET_{c_i} + ET_{\{o_i\}} * LR - eff_i - awc_i$$

where i is the month, CWN_i is the monthly aggregated crop water need (mm), ETc_i is the product of the monthly ET_{oi} and k_{ci} from the previous sections (mm), LR is the percentage of leaching requirements (%), eff_i is the monthly effective rainfall (mm) and awc_i the monthly available water content (mm).

When rain falls on the soil surface, some of it infiltrates into the soil, some stagnate on the surface, while some flows over the surface as runoff. Of the water that infiltrates into the soil, some percolates below the root zone, while the rest remains stored in the root zone. Effective rainfall is the amount of the rainwater which can be retained in the root zone and can be used by a plant, which means the total rainfall minus runoff, minus evaporation, minus deep percolation. The following empirical correlation was used to calculate effective rainfall on a monthly basis [22]:

$$eff_i = f * 1.253 * P^{0.824} - 2.935 * 10^{0.001 * ET_p}$$

where eff_i is the effective rainfall per month (mm), P is the total precipitation per month (mm), ET_p is the total crop evapotranspiration per month (mm) and f a correlation factor which depends on the depth of irrigation water application (dimensionless). Factor f is 1.0 if the irrigation water application depth (D_a) is 75 mm, as will be assumed, and otherwise:

$$f = 0.133 + 0.201 * lnDa \text{ if } D_a < 75\text{mm}$$

$$f = 0.946 + 7.3 * 10^{-4} * D_a \text{ if } D_a >= 75\text{mm}$$

Available water content (awc) or maximum soil water deficit is the maximum amount of water stored in the plant's root zone that is readily available for use [23]. Since the NWSAS area is located in the arid bioclimatic stage (hyper-arid) where rainfall is very irregular and often exceptional causing floods. Therefore the available water content (awc) in the soil is assumed insignificant [24] and the Irrigation water need is dependent on crop evapotranspiration and effective rainfall.

Peak crop water demand (PWD) is one of the most important design criteria of an irrigation scheme since it determines the size of the required pump and the distribution system and therefore the operational power demand for the irrigation scheme. The maximum discharge (in $m^3/d/ha$ or l/s/ha) is the rate at which water must flow to meet peak demand [21]. Pipes, canals or channels must be large enough to carry this discharge and the pump and power unit must be capable to deliver the discharge at the pressure required. Due to the high variation of the demand throughout the season, the peak requirement might be at least double the average daily water needs. The following equations were used for units conversion and preparing the data for the next steps [21]:

$$Monthly\ crop\ water\ needs\ (m^3/ha) = CWN_i\ (mm) * 10$$

$$Average\ daily\ crop\ water\ needs\ (m^3/d/ha) = monthly\ crop\ water\ needs\ (m^3/ha) * 30$$

$$Peak\ crop\ water\ requirement\ (m^3/d/ha) = averagedaily\ crop\ water\ needs\ (m^3/d/ha) * 2$$

Since discharge in $m^3/d/ha$ is not a very convenient unit to use for design purposes, a more common unit is l/s/ha, calculated as follows:

$$Peak\ crop\ water\ requirement\ (l/s/ha) = peak\ crop\ water\ requirement\ (m^3/d/ha) * 0.012$$

The peak scheme water demand is the discharge in litres per second (l/s) required to meet the peak crop water needs, plus the losses which occur in field application and the distribution system. The overall loss is called irrigation efficiency and can be calculated by:

$$Irrigation\ efficiency\ \% = field\ application\ efficiency * distribution\ efficiency * 100$$

Peak water demand (PWD) can be calculated as:

$$Peak\ water\ demand\ (l/s/ha) = peak\ crop\ water\ requirments\ (l/s/ha) * irrigation\ efficiency$$

This discharge in l/s/ha is called duty and assumes that 1 ha of land is being irrigated and the system will be running 24 hours every day to meet the water demand. The irrigated area in each grid cell was used from the resulting calibration process and the pump operating time was assumed 10 hrs a day and the following equation was used:

$$Peak\ scheme\ water\ demand\ (l/s) = \frac{Peak\ water\ demand\ (l/s/ha) * cropped\ area\ (ha) * 24}{hours\ of\ operation\ (h)}$$

Seasonal scheme water demand (m^3) refers to the amount/volume of water needed over a season, taking into account the water losses in the distribution system and in field application [21]. Furthermore, it is one of the key parameters for the estimation of the electricity demand required for pumping over a season as it will be explained in the following section.

$$Seasonal\ scheme\ water\ demand\ m^3 = Monthly\ crop\ water\ needs\ \left(\frac{m^3}{ha}\right) * cropped\ area\ (h) * irrigation\ efficiency$$

1.4 Estimation of the energy requirement for pumping

Energy for pumping or energy for irrigation purposes can be expressed as the energy required to lift the water from the groundwater source and to overcome friction in pipes, pumps, and other elements of the distribution system used for conveyance of the water across the land surface Electrical energy or electricity (kWh) is expended when a unit volume (m^3) of water passes through a pump during its

operation [25]. Essentially a linear relationship exists between the electricity intensity value for groundwater pumping and the depth from which it is pumped at a specific pressure [26].
As mentioned earlier, the electricity demand depends on the efficiency of the pump, the pipeline line and diameter, pipe material roughness or friction factor, and the volumetric demand for water. As shown in the following function for electricity demand, E_D (kWh):

$$E_D = f(d, Q, P, t, f_l)$$

where *d* is the distance through which the water is to be lifted, *Q* is the required volumetric amount of water for pumping, *P* is the pressure required at the point of use, *t* is the time over which the water is pumped (assuming a constant head), and f_l is the friction loss along the distance *d* within the distribution system.
The calculation of the electricity demand (ED_{gw} in kWh) for pumping water from groundwater resources, can be calculated as follows:

$$ED_{gw} kWh_1 = \frac{Seasonal\ scheme\ water\ demand\ m^3 * TDH_{gw}(m) * 0.00272}{PP_{eff}(\%)}$$

where *Seasonal scheme water demand* (m^3) was defined in the previous section as the total volume of water required pumping over a selected season, the constant 0.00272 kWh/m^3 per m of lifting, is simply water density times gravity. TDH_{gw} *(mm)* represents the Total Dynamic Head and PP_{eff} *(%)* accounts for the Pumping Plant efficiency.
The calculation of the Total Dynamic Head is estimated using the following equation:

$$TDH_{gw}\ (m) = EL(m) + SL(m) + OP(m) + FL(m)$$

where *EL (m)* is the Elevation Lift, the sum of the depth to the groundwater level of water and of the water table or drawdown, *SL (m)* expresses the Suction Lift which is assumed to be zero in groundwater vertical pumping, *OP (m)* stands for Operating Pressure and accounts for the pressure needed based on the application and conveyance system, and *FL (m)* expresses the Friction Losses in the piping systems. In this indicative study and for the sake of simplicity the TDH is assumed to equal the water table depth (m) since other parameters were assumed zero as no data was available on the average conveyance system or the piping systems.
The equation used for the estimation of the Pumping Plant efficiency is given below:

$$PP_{eff}(\%) = fuel\ efficiency * power\ unit\ efficiency * transmission\ efficiency \\ * pump\ efficiency * 100\%$$

The above electricity demand is also validated and suggested, in a different form, by [21], where the overall electricity need over a period of time is given by the equation:

$$ED_{gw} kWh = \frac{Seasonal\ scheme\ water\ demand\ m^3 * TDHgw(m)}{367 * PP_{eff}(\%)}$$

where the multiplier (1/367) is equal to 0.0027.
Finally, the overall power demand for pumping water from the underground is determined using the equation adapted from the aforementioned FAO manual:

$$PD_{gw}\ kW = \left[9.81 * discharge\left(\frac{m^3}{s}\right) * TDH_{gw}(m)\right] / PP_{eff}(\%)$$

Where: *discharge (m^3/s)* is the *Peak scheme water demand (l/s)* expressed in m^3/s.

1.5 Estimation of the least-cost electricity supply option

After estimating the electricity requirement for water pumping and desalination, this section will focus on the supply side and will compare different supply options based on the Levelized Cost of Electricity (LCOE). This is done following a similar approach to [27]. In practice, this calculation maps the cheapest option available to the farmer at each location of the NWSAS basin to produce electricity for pumping. If the farm is far from the grid, this means what is the cheapest off-grid option (diesel or renewable?). If the farm is close and can connect to the grid, this means what is the cheapest supply option to power pumps (diesel, renewables or electricity from the gird)?

The LCOE is a life-cycle cost concept that accounts for all the expenses (investment costs, operating and maintenance costs, fuel cost) with the revenues generated from electricity generation sales over the lifetime of the power plant or the small-scale installation. It accounts for all physical assets and resources required to deliver one unit of electricity output [28].

$$LCOE = \frac{\sum_{t=1}^{n} \frac{I_t + O\&M_t + F_t}{(1+r)^t}}{\sum_{t=1}^{n} \frac{E_t}{(1+r)^t}}$$

Where I_t: Investment expenditure for a specific system in year t, $O\&M_t$: the operation and maintenance costs, F_t: the fuel expenditures, E_t: the generated electricity, r: the discount rate, n: the lifetime of the system.

Different supply options are currently being used in each country. A mix of diesel and electric pumps are used in the three countries, however, due to lack of publicly available data, we assume that all pumps in Algeria and Tunisia are running with diesel generators[3] and that in Libya all pumps are powered by the grid, because of consultation with local experts. These options were compared to stand-alone PV and small-scale wind turbines, using the LCOE as a reference for comparison as shown in Table 6.

[3] Medium and low voltage lines network maps for the three countries are not available publicly. Therefore, it was difficult to map the distribution of the electric pumps in Algeria and Tunisia where they use a mix of diesel and electric pumps.

1. Additional results

2.1 Cropland Calibration

The original and calibrated cropland density maps are shown in Figure S7 and Figure S8: and a comparison between the original ESA CCI dataset, the national statistic and the calibrated cropland layer is presented in Figure 4 (in the main manuscript).

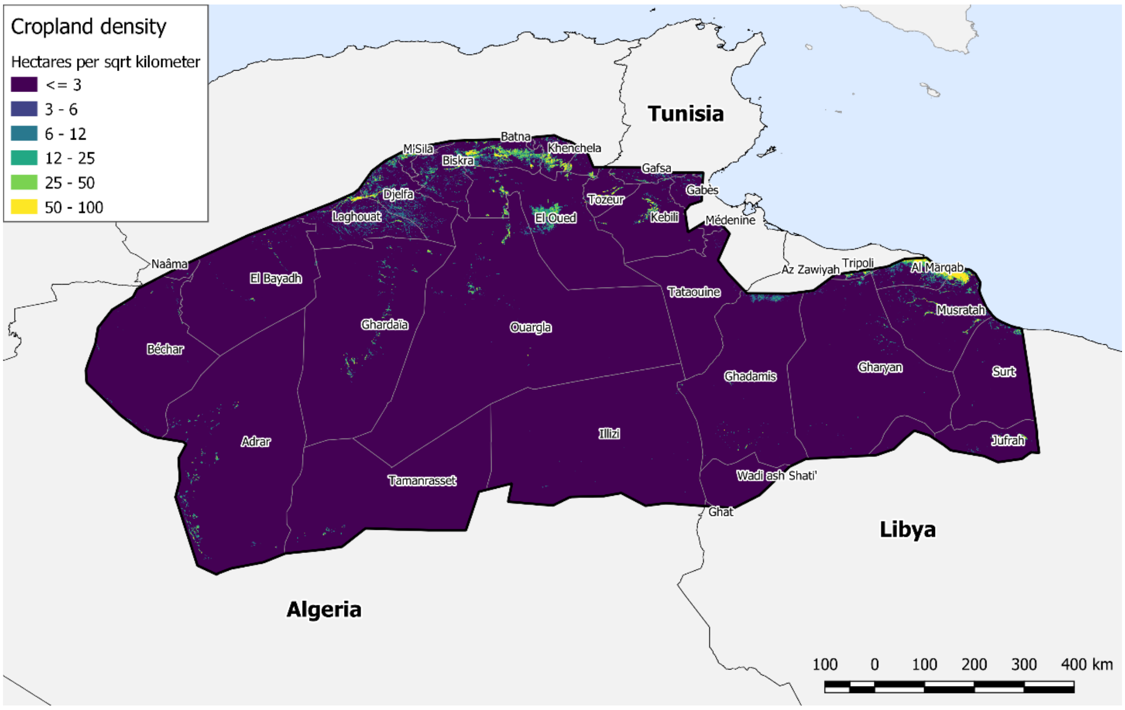

Figure S7. ESA CCI uncalibrated cropland map.

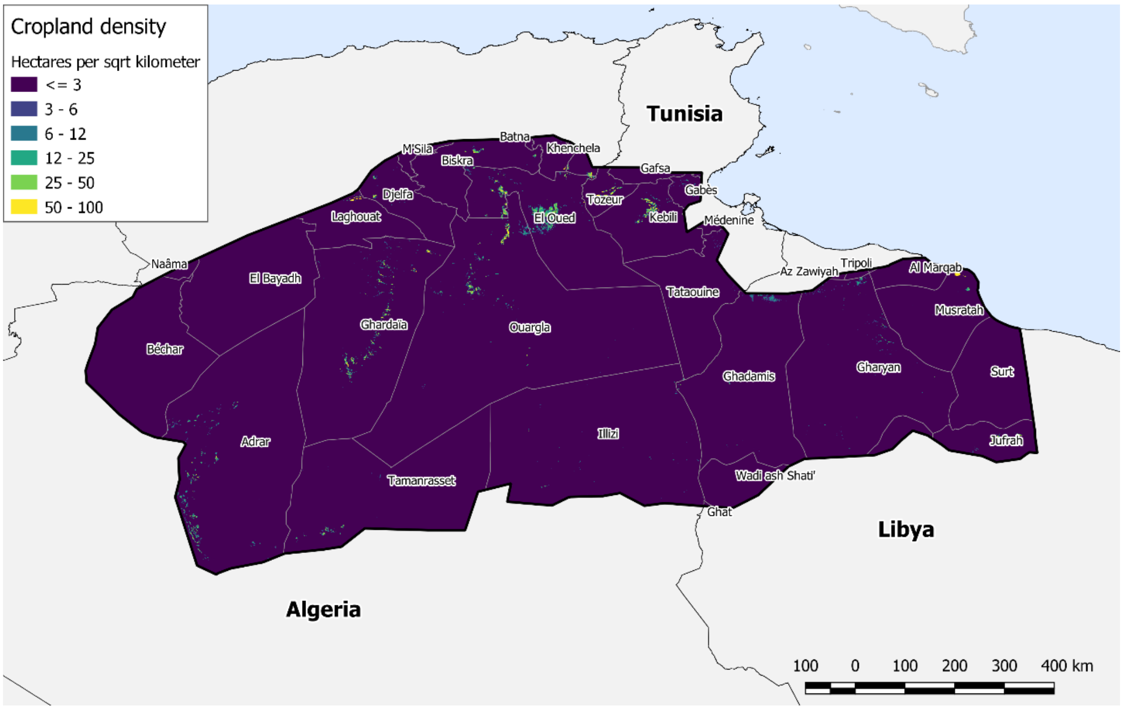

Figure S8. Calibrated cropland map

2.2 Estimated water demand for different irrigation technique

Table S7. Comparison of estimated water demand for each irrigation technique (scenario) and the water-saving due to improved efficiency, all values are in (m^3/ha).

	Province	Scenario 1: Surface Irrigation – low efficiency	Scenario 2: Surface Irrigation – Medium efficiency	Scenario 3: Drip Irrigation – High efficiency	Savings (low-med)	Savings (low-high)
Algeria	Adrar	15 794	10 934	8 361	4 860	7 432
	Biskra	10 034	6 946	5 312	3 087	4 722
	Djelfa	10 303	7 133	5 455	3 170	4 849
	El Oued	11 470	7 941	6 072	3 529	5 398
	Ghardaia	12 775	8 844	6 763	3 931	6 012
	Illizi	14 170	9 810	7 502	4 360	6 668
	Khenchela	10 831	7 498	5 734	3 332	5 097
	Laghouat	10 085	6 982	5 339	3 103	4 746
	Ouargla	12 379	8 570	6 554	3 809	5 825
	Tamanrasset	15 656	10 839	8 289	4 817	7 368
	Tebessa	10 927	7 565	5 785	3 362	5 142
Libya	Ghadamis	10 515	7 280	5 567	3 236	4 948
	Gharyan	10 819	7 490	5 728	3 329	5 091
	Jufrah	15 113	10 463	8 001	4 650	7 112
	Musrata	8 891	6 155	4 707	2 736	4 184
Tunisia	Gabes	10 074	6 974	5 333	3 100	4 741
	Kebili	11 207	7 759	5 933	3 448	5 274
	Tataouine	10 216	7 072	5 408	3 143	4 807
	Tozeur	10 794	7 473	5 715	3 321	5 080

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