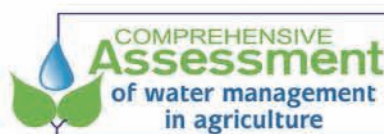
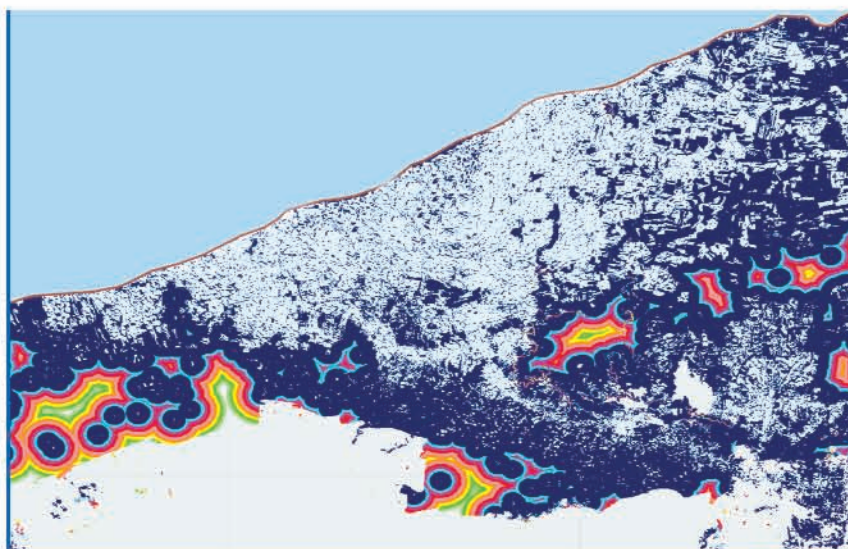


Spatial Modeling of the Biophysical Potential for Supplemental Irrigation

A Case Study in Syria

EDDY DE PAUW
THEIB OWEIS
BASHAR NSEIR
JAWAD YOUSSEF



International Center for Agricultural
Research in the Dry Areas

About ICARDA and the CGIAR



Established in 1977, the International Center for Agricultural Research in the Dry Areas (ICARDA) is one of 15 centers supported by the CGIAR. ICARDA's mission is to improve the welfare of poor people through research and training in dry areas of the developing world, by increasing the production, productivity and nutritional quality of food, while preserving and enhancing the natural resource base.

ICARDA serves the entire developing world for the improvement of lentil, barley and faba bean; all dry-area developing countries for the improvement of on-farm water-use efficiency, rangeland and small-ruminant production; and the Central and West Asia and North Africa (CWANA) region for the improvement of bread and durum wheats, chickpea, pasture and forage legumes, and farming systems. ICARDA's research provides global benefits of poverty alleviation through productivity improvements integrated with sustainable natural-resource management practices. ICARDA meets this challenge through research, training, and dissemination of information in partnership with the national, regional and international agricultural research and development systems.



The Consultative Group on International Agricultural Research (CGIAR) is a strategic alliance of countries, international and regional organizations, and private foundations supporting 15 international agricultural Centers that work with national agricultural research systems and civil society organizations including the private sector. The alliance mobilizes agricultural science to reduce poverty, foster human well being, promote agricultural growth and protect the environment. The CGIAR generates global public goods that are available to all.

The World Bank, the Food and Agriculture Organization of the United Nations (FAO), the United Nations Development Programme (UNDP), and the International Fund for Agricultural Development (IFAD) are cosponsors of the CGIAR. The World Bank provides the CGIAR with a System Office in Washington, DC. A Science Council, with its Secretariat at FAO in Rome, assists the System in the development of its research program.

Spatial Modeling of the Biophysical Potential for Supplemental Irrigation

A Case Study in Syria

Eddy De Pauw, Theib Oweis, Bashar Nseir , and Jawad Youssef



International Center for Agricultural Research in the Dry Areas

Copyright © 2008 ICARDA (International Center for Agricultural Research in the Dry Areas)

All rights reserved.

ICARDA encourages fair use of this material for non-commercial purposes, with proper citation.

Citation:

Eddy De Pauw, Theib Oweis, Bashar Nseir , and Jawad Youssef. 2008. Spatial modeling of biophysical potential for supplemental irrigation: case study in Syria. ICARDA, Aleppo, Syria. vi + 26 pp.

ISBN: 92-9127-208-4

International Center for Agricultural Research in the Dry Areas (ICARDA)

P.O. Box 5466, Aleppo, Syria.

Tel: (963-21) 2225112, 2225012, 2213433, 2213477

Fax: (963-21) 2225105, 2213490

E-mail: ICARDA@cgiar.org

Website: www.icarda.org

The views expressed are those of the authors, and not necessarily those of ICARDA. Where trade names are used, it does not imply endorsement of, or discrimination against, any product by the Center. Maps have been used to support research data, and are not intended to show political boundaries.

This report is an output of the project ‘Assessment of Water Harvesting and Supplemental Irrigation Potential in Arid and Semi-Arid Areas of West Asia and North Africa’, funded through the CGIAR initiative on Comprehensive Assessment of Water Management in Agriculture. It describes results from Activity 8 of the project: Development and testing of methodologies and models for country-level identification of areas with potential for water harvesting and supplemental irrigation.

ACKNOWLEDGMENTS

The authors are pleased to thank Dr. Adriana Bruggeman for her – as usual – very helpful suggestions and critical comments.

CONTENTS

	Abstract	v
1	Introduction	1
2	Methodology	1
	2.1 General approach	1
	2.2. Computing water savings	2
	2.2.1 Principle	2
	2.2.2 Equations	2
	2.2.3 Calculating total water savings from an irrigated area	2
	2.3 Allocating water savings to rainfed areas	2
	2.3.1 General approach	2
	2.3.2 Prioritizing water allocations through multi-criteria evaluation	3
	2.4 Use of remote sensing for generating land use/land cover layers	6
	2.4.1 Satellite platform and image analysis	6
	2.4.2 Identifying surface water bodies	6
	2.4.3 Identifying forest areas	6
	2.4.4 Identifying irrigated areas	6
	2.4.5 Identifying arable areas	7
	2.5 Spatial modeling	7
	2.5.1 General approach	7
	2.5.2 Input databases	9
	2.5.3 Intermediate layers	12
	2.5.4 Allocating water savings	12
3	Results	14
4	Potential for outscaling	18
5	Future work	19
	References	20
Annex 1	Landsat imagery paths and rows	21
Annex 2	LANDSAT image processing for identification of water bodies	21
Annex 3	LANDSAT image processing for identification of forest areas	22
Annex 4	LANDSAT image processing for identification of irrigated areas	22
Annex 5	LANDSAT image processing for identification of arable land	23
Annex 6	Spatial Water Allocation Algorithm	24
Annex 7	Maps	27

ABSTRACT

This study describes a modeling methodology for using Geographic Information Systems (GIS) tools to identify potential areas for the introduction of supplemental irrigation. In their most simple concept, such areas would be characterized by the presence of arable soils, non-constraining slopes, agricultural land use, and would be within proximity of existing irrigation schemes, so that water conveyance or pumping costs are not uneconomical.

The method is based on the combination of a simple model to calculate the possible water savings – made by the shift from spring/summer fully-irrigated crops to supplemental-irrigated winter/spring crops – with a water allocation procedure for the surrounding rainfed areas based on suitability criteria.

The water savings within an irrigated area (the 'water bank') were obtained as the difference in total crop water need between a standard fully irrigated crop (cotton) and a standard partially irrigated crop (wheat), calculated by textbook methods for crop water requirements, summed for all pixels inside the irrigated area.

These potential water savings from irrigated areas were then allocated to neighboring rainfed areas, using an allocation procedure that reflects the suitability of areas surrounding an irrigation perimeter to benefit from a possible water allocation. The criteria used were based on distance from the irrigated perimeter, slope, soils, and presence of forests. The scores obtained against these four criteria were combined in a multi-criteria evaluation using the principle of the most limiting factor. The results of the multi-criteria evaluation were retained in an 'Allocation Priority Layer' (APL) specific to each irrigated perimeter. Water was then allocated to the rainfed areas in an iterative

process, first to the pixels with the highest scores in the APL, and as these filled up, to pixels with lower priority scores until the water bank for each perimeter was exhausted.

In order to model the complex relationships between irrigated and rainfed areas, a Spatial Water Allocation Algorithm was developed as a stand-alone Visual Basic program operating on data layers consisting of climate surfaces, classified Landsat imagery and the SRTM digital elevation model. Three types of areas – areas irrigated in summer, forest areas and arable land – were identified using Landsat imagery, combined with supervised classification methods. Forest areas were considered a prohibitive constraint, whereas the land use category 'arable land' was, in the absence of good soils maps, a proxy for 'suitable soils'.

This modeling exercise suggests that Syria has a large potential for supplemental irrigation by shifting from a fully irrigated summer crop to a partially irrigated winter-spring crop. This potential amounts roughly to a more than doubling of the area under irrigation at any given time.

The methodology can be applied in other dry-land areas without major modifications. The factors, decision rules and thresholds that determine suitability and water allocation priorities can be adjusted to local conditions. The data requirements include data layers related to precipitation and evapotranspiration, a digital elevation model, land use/land cover and soil maps, or, in their absence, these factors derived from satellite imagery.

Future work will include testing of this methodology, and its incorporation into a decision-support system that allows user control in developing relevant scenarios for change, which may differ from place to place.

1. INTRODUCTION

Supplemental irrigation is the addition of water to essentially rainfed crops during times of serious rainfall deficits. The conjunctive use of rainfall and irrigation water is a potentially valuable management principle under conditions of water scarcity. The aim is to reduce risk of crop failure, where rainfall is normally sufficient but vulnerability to drought is high, and thus to stabilize yields.

As demonstrated by Oweis et al. (2000), the water use efficiency of supplemental irrigation in Mediterranean dryland environments can be much higher than that of full irrigation, especially if the latter is provided during the summer months, when precipitation is minimal and water requirements high due to elevated temperatures.

Given specific irrigation schemes, where the area under summer irrigation is known, it is possible to estimate the potential water savings by changing irrigation systems or cropping patterns to make more frugal use of irrigation water. Ballpark figures (e.g. Table 1) already indicate the magnitude of the water savings that could be achieved by simply switching cropping patterns that depend mainly on summer irrigation, with little or no precipitation additions, to systems in which precipitation is complemented by additional irrigation water.

However, if such changes were indeed implemented, it is not so evident where the potential savings could eventually be applied. Apart from social and economic considerations, there are constraints related to land quality (particularly the need for suitable soils and slopes), distance from the irrigated areas, regulated land use conversions (e.g. forest to arable land), differences in elevation etc.

The objective of this study is to apply Geographic Information Systems (GIS) tools for identifying potential areas that would be prime candidates for government programs to introduce supplemental irrigation. In their most simple concept, such areas would be characterized by the presence of arable soils, non-constraining

slopes, agricultural land use, and where distance from, or an elevation difference with, existing irrigation schemes does not impose uneconomical costs of water conveyance or pumping. Another typical question agricultural planners might ask is how much land within the existing irrigation schemes would need to shift to supplemental irrigation systems in order to provide supplemental irrigation to all the suitable land in the neighborhood of an existing scheme.

The methodology developed in this study can be used to identify suitable areas by integrating existing information, derived from either thematic maps or satellite imagery, in a GIS. This methodology is outlined in the following sections.

2. METHODOLOGY

2.1. General approach

Imagine an irrigation scheme, with crops mostly grown in summer. In order to assess the impact of a shift from full summer irrigation to supplemental irrigation of winter-spring crops, the first step is to estimate the water savings that could be achieved, first within each area unit (pixel) of the irrigated area, and then the total savings for the irrigated area or for a specified fraction of the area (the 'water bank').

The second step is to distribute these water savings among pixels that at present are not irrigated but meet specified criteria of soil, terrain and land use suitability, and are within an acceptable distance from the currently irrigated areas. Distribution rules need to be established that emulate **allocation priorities**. A simple distribution rule would be one in which those pixels that score best against the different criteria, are filled up first, followed by those that score less well, etc. A second distribution rule could be to fill up the pixels, in accordance with the allocation priorities established by Rule 1, with a user-specified fraction of the water requirement that is not met by precipitation (Rule 2). Further rules could be put in place, but Rules 1 and 2 are sufficiently powerful to simulate fairly complex realities. The actual procedures for calculating water savings and reallocating them are described in the next sections.

2.2. Computing water savings

2.2.1. Principle

The **water savings** are calculated as the difference in total crop water need that could be achieved by shifting from a standard irrigated crop, planted in spring and grown during summer and early autumn (cotton), to a standard crop, planted in autumn and grown by precipitation supplemented by irrigation during late autumn, winter and spring (wheat).

The crop water needs for both systems are estimated by using the simple relationships, proposed by Allen et al. (1998), between crop coefficients (k_c) and potential evapotranspiration, calculated by the Penman-Monteith method, during the growth cycles for the respective crops.

The standard crop coefficients and growth cycles for winter wheat and cotton are shown in Fig. 1. The standard crop coefficient values,

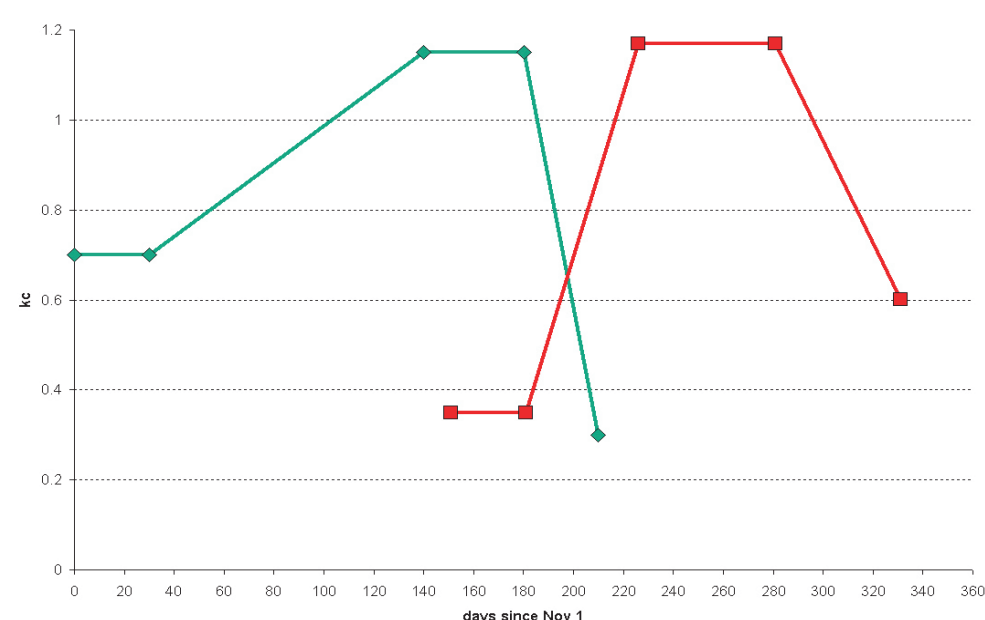


Figure 1. Standard crop coefficients in relation to growth stages for winter wheat and cotton

obtained from Allen et al. (1998) and adjusted growth periods for both crops, adapted to Syrian conditions, are shown in Table 1.

2.2.2. Equations

For an individual pixel the following equations can be used to determine the potential water savings obtained by a shift from a reference summer-fully irrigated crop to a reference winter-supplemental irrigated crop:

2.2.3. Calculating total water savings from an irrigated area

The total potential water savings (TWS) in each irrigated area is calculated as the sum of water savings from all irrigated pixels within that irrigated area.

Henceforward an irrigated area that is spatially contiguous will be called 'irrigated perimeter'. An irrigated perimeter can be very large, but also as small as a single pixel. In this study only irrigated areas larger than 50 pixels (about 45 ha) have been considered. The smaller ones were disregarded in view of the vast amount of calculations required to process all irrigated perimeters (see further).

2.3. Allocating water savings to rainfed areas

2.3.1. General approach

After a TWS has been calculated for each irrigated perimeter, an allocation procedure is required. The process is based on the combination of various criteria that in conjunction determine allocation priorities. Allocation of water to pixels currently not irrigated is then modeled on the basis of these allocation priorities.

Table 1. Comparison of crop coefficients for wheat and cotton

Wheat			Cotton		
Days after planting	Days after Nov 1	k_c	Days after planting	Days after Nov 1	k_c
0	0	0.7	0	151	0.35
30	30	0.7	30	181	0.35
140	140	1.15	75	226	1.17
180	180	1.15	130	281	1.17
210	210	0.3	180	331	0.6

The criteria used for allocating water refer to the suitability of areas surrounding an irrigation perimeter to benefit from a possible water allocation, based on distance from the perimeter, slope, soils, and presence of forests. The scores obtained against these four criteria are

$$ETc_t = kc * ET0_t \quad (1)$$

$$ETc_{irr,cotton} = \sum_t ETc_t - \sum_t Prec_t \quad (2)$$

$$ETc_{irr,wheat} = (\sum_t ETc_t - \sum_t Prec_t) * INSI \quad (3)$$

$$PWS = ETc_{irr,cotton} - ETc_{irr,wheat} \quad (4)$$

combined in a multi-criteria evaluation using the *Principle of the Maximum Limitation*: since the criteria can, for practical purposes, be considered independent, the score of the most limiting factor is retained.

The results of the multi-criteria evaluation are retained in an *Allocation Priority Layer* (APL) specific to each irrigated perimeter. Water is then allocated in an iterative process, first to the pixels with the highest scores in the APL, and as these fill up, to pixels with lower priority scores until the TWS for each perimeter is exhausted.

2.3.2. Prioritizing water allocations through multi-criteria evaluation

The criteria used include distance from the perimeter, presence of acceptable slopes, favorable soils and absence of forests. The very simple rules that allow translating values for these factors into suitability scores are explained in this section.

Distance rule

The suitability for supplemental irrigation decreases with distance from a fully irrigated area. Up to a certain distance from the perimeter, costs of transferring water can be considered similar as within the perimeter, whereas at a maximum distance they become prohibitive. In between, costs increase proportionally with distance. These conditions can be captured by the following rules:

- if distance $\geq b$, $S_{dist} = 0$
- if distance $\leq a$, $S_{dist} = 1$
- if distance between a and b ,
 $S_{dist} = (b - \text{distance}) / (b - a)$

where S_{dist} = suitability score for distance

Currently $a = 1$ km, $b = 5$ km, based on expert opinion.

Table 2. Example of potential water saving calculations

Cotton							
Date	Date after 1 Nov	kc	ETo	ETc	Prec	ETc _{irr}	Potential water savings
15 Apr	166	0.35	123	43	34		
15 May	197	0.64	193	124	19		
15 Jun	227	1.17	267	312	2		
15 Jul	258	1.17	308	360	0		
15 Aug	289	1.08	274	296	0		
15 Sep	319	0.74	178	131	1		
				1266	56	1210	1056
Wheat							
Date	Date after 1 Nov	kc	ETo	ETc	Prec	ETc _{irr}	Water allocation needs
15 Nov	15	0.70	40	28	36		
15 Dec	45	0.76	21	16	59		
15 Jan	76	0.89	22	20	60		
15 Feb	107	1.02	37	38	51		
15 Mar	135	1.13	72	81	45		
15 Apr	166	1.15	123	141	34		
15 May	196	0.70	193	134	19		
				458	304	154	154
INSI	1						

Crop coefficient values have been interpolated between the average values for each growth stage (Table 1), to coincide with the mid-points of each month of the growth cycle.

Slope rule

Supplemental irrigation, as any irrigation method, requires suitable slopes. Since this study is not a comparison of different irrigation methods (e.g. gravity versus sprinkler or drip), ballpark thresholds for slope suitability have been retained and applied in the following rules:

- if slope $\geq b$, $S_{\text{slope}} = 0$
- if slope $\leq a$, $S_{\text{slope}} = 1$
- if slope between a and b ,
 $S_{\text{slope}} = (b - \text{slope}) / (b - a)$

S_{slope} = suitability score for slope

Currently $a = 5\%$, $b = 20\%$, based on expert opinion (Fig. 2).

The principle is again that below a minimum slope, the factor is not considered prohibitive, whereas above a maximum slope, the factor is totally prohibitive, irrespective of the scores on the other factors. For slopes between the minimum and the maximum, the suitability scores decrease proportionally with the slope.

Soil rule

In order to make the investment in water transfer and application worthwhile, it is obvious that the soils must be suitable for agriculture, otherwise no irrigation will occur. For this study we have decided to use direct evidence for soil suitability rather than indirect evidence (from a soil map). The direct evidence for 'suitable soils' is in the presence of fields with crops ('arable land') and can be obtained through remote sensing. The soil rule ('presence of suitable soils') can then be restated as 'presence of arable land':

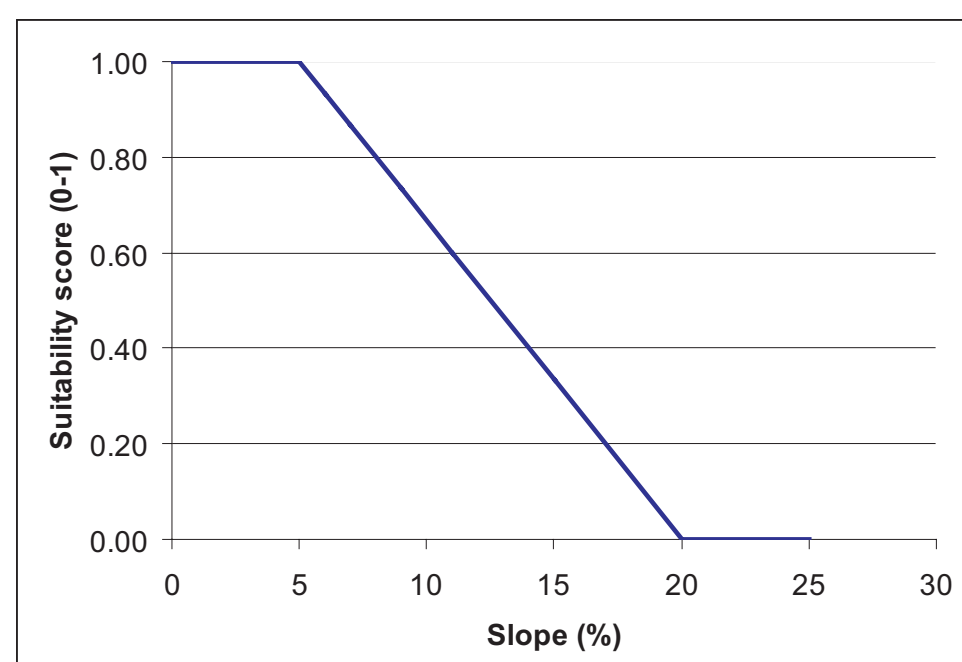


Figure 2. Suitability scores as a function of slope

- if arable land = 1 (the pixel represents arable land) the soil is suitable ($S_{\text{soil}} = 1$)
- if arable land = 0 (pixel represents non-arable land) the soil is unsuitable ($S_{\text{soil}} = 0$)

where S_{soil} = suitability score for soil

There are two reasons for using direct evidence of soil suitability. The first reason is the low resolution of the Soil Map of Syria (Louis Berger et al., 1982). Designed at a scale of 1:500,000, the mapping units are in fact soil associations and the location of individual soil types within the mapping units is unknown. The soils are classified in a soil taxonomic system (Soil Survey Staff, 1975) and the link with suitability for agriculture is circumstantial. It is therefore not surprising that several studies (e.g. Cools et al., 2003) have demonstrated that suitability derived from such sources, or from expert-inferred relationships between soil properties and crop productivity, does not always correspond with reality. This is quite obvious in the case of soils with strong gypsum content. According to different authorities on crop ecological constraints, high amounts of gypsum render soils marginal or unsuitable for many crops (Table 3).

Fig. 3 shows the distribution of soils with strong gypsum content in Syria, derived from the Soil Map of Syria (Van de Steeg et al., 2004). Fig. 4 zooms into an area in which both irrigation and gypsic soils do occur. Fig. 4a shows the irrigated area and Fig. 4b the area that is both irrigated and has gypsic soils. It is clear that the gypsum problem is less severe in areas that are actually irrigated (hence suitable for irrigation) than would be expected from the ex-ante suitability evaluation. We therefore decided not to consider gypsum as a major limiting factor for agriculture, once irrigation water becomes available.

Table 3. Gypsum percentages marginally suitable (S3) or unsuitable (N) for some crops

Crop	S3	N
Citrus	>3 %	>5 %
Cotton	>10 %	>15 %
Barley, maize, sunflower, wheat	>10 %	>20 %
Olive	>20 %	>25 %

Source: Sys et al., 1993

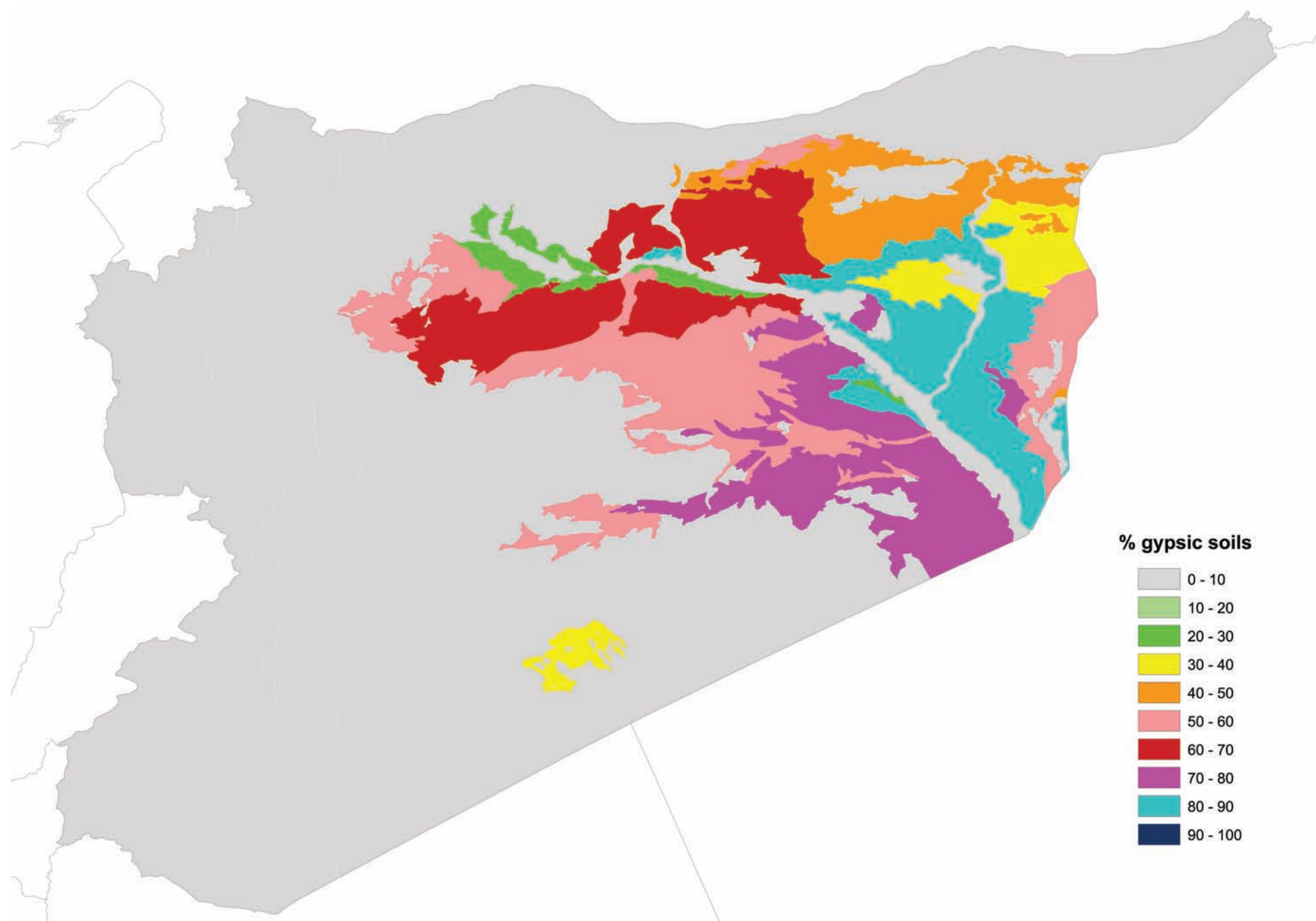


Figure 3. Areas with soils with high gypsum content



Figure 4. Irrigated areas (a); areas that are both irrigated and under Gypsisols (b)

Forest rule

Forests and irrigation for crops are mutually exclusive. The presence of forests, also detectable from remote sensing (see section 2.4.3) therefore creates a constraint for the introduction of supplemental irrigation:

- if forest = 0 (the pixel represents non-forest), the land use is **suitable** ($S_{\text{forest}} = 1$)
 - if forest = 1 (the pixel represents forest), the land use is **unsuitable** ($S_{\text{forest}} = 0$)
- where S_{forest} = suitability score for forest presence

The scores on the four individual factors are then combined using the Most Limiting Factor rule:

$$S = \text{Min} (S_{\text{dist}}, S_{\text{slope}}, S_{\text{soil}}, S_{\text{forest}})$$

S = final suitability score, Min = lowest of the individual suitability scores

2.4. Use of remote sensing for generating land use/land cover layers

Existing land cover is a key factor deciding whether or not supplemental irrigation is feasible. As discussed in the previous section, forests are a prohibitive constraint, whereas the location of irrigated and arable land is essential to model where expansion of supplemental irrigation could occur. These land cover types were all identified through remote sensing, as discussed in the next section.

2.4.1. Satellite platform and image analysis

Twelve rectified and UTM-projected Landsat ETM scenes, taken in two different seasons (summer 2002, spring 2003) covering the whole area of Syria, were used to extract the land cover features required in the spatial modeling (see section 2.5). Annex 1 shows the path and row locations of the images used. Image processing was undertaken using ERDAS Imagine software and some functions of the ArcGIS 8.3 ESRI software.

Principal Components Analysis (PCA) was central in the identification of most land cover categories. PCA is often used as a method of data compression. It allows redundant information to be compacted into fewer bands, in the case of Landsat from 8 bands to 3-4. The bands of PCA data are uncorrelated and independent,

and are often easier to interpret than the source data.

2.4.2. Identifying surface water bodies

Surface water bodies were easy to recognize and classify from satellite images due to the spectral characteristics of water. Longer wavelengths in the visible and near infrared (NIR) spectrum are absorbed more by water than shorter wavelengths. Consequently, the NIR band 4 of the ETM imagery gives adequate spectral information on water bodies, although they might sometimes be confused with shaded areas, which have a similar spectral response.

Identification of surface water locations was based in this study on two main methods, unsupervised classification and PCA with different class settings per image. This was necessary owing to differences in spectral characteristics and complexity of landscape patterns in each image. Annex 2 provides details on the particular settings used for each analyzed ETM image. Fig. 5 illustrates the use of both approaches in this study.

2.4.3. Identifying forest areas

Forest areas have not been easy patterns to identify and map consistently, due to a high level of fragmentation and mosaicing with other land cover categories. Forests in Syria are mainly coniferous and occur mostly in Agricultural Stability Zones 1 and 2, which receive higher amounts of precipitation than other stability zones. They show up with a darker green than irrigated fields and natural vegetation.

Forests have been mapped using Principal Component Analysis (PCA), after blocking out the areas containing forests in western Syria.

The region-group filter in ArcGIS was used to identify contiguous blocks of pixels. Pixel blocks that were considered too small for the analysis or possibly noise due to the particular classification technique, were removed. Fig. 6 illustrates the approach, while Annex 3 provides details for each scene.

2.4.4. Identifying irrigated areas

Irrigated areas are easy to recognize in summer satellite images due to their presence as green agricultural fields in the dry season and their

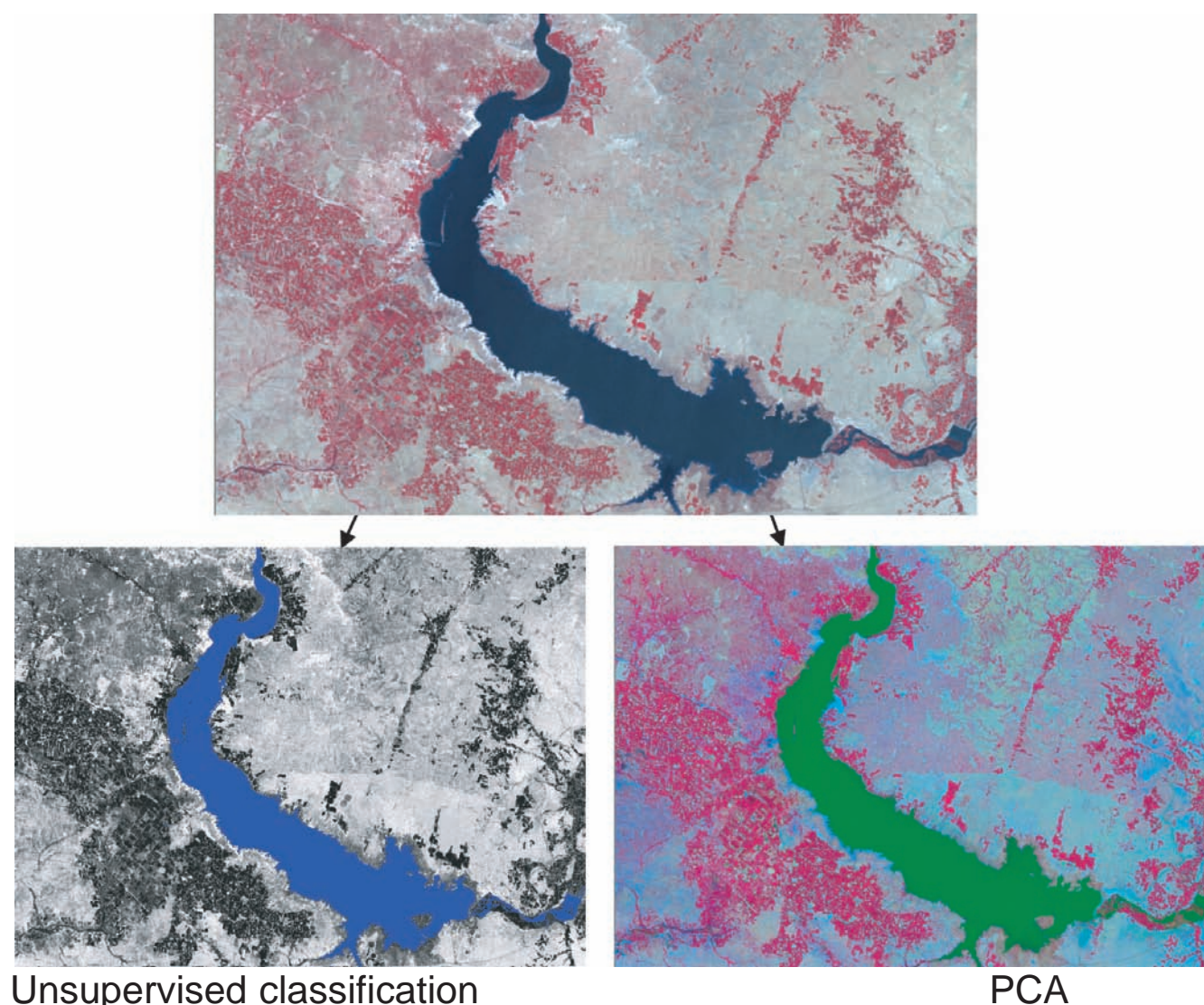


Figure 5. Use of unsupervised classification and PCA for mapping water bodies

regular patterns. After having extracted the forest areas in western Syria, as mentioned in section 2.4.3., the Normalized Difference Vegetation Index (NDVI) technique was applied to identify and map irrigated fields. Fig. 7 illustrates the use of the NDVI technique, whereas Annex 4 provides details on the particular thresholds used for each scene.

2.4.5. Identifying arable areas

Arable areas were the hardest pattern to assign and map using automated image analysis procedures due to the undefined variation range of spectral characteristics of the land surfaces containing agricultural fields and their current state of vegetation cover (cultivated, previously cultivated and fallow).

For mapping the arable areas in Syria, the results were obtained from the different analyses based on NDVI, visual interpretation and complementary GIS processing, as explained in Annex 5. Fig. 8 illustrates the steps involved.

The differences in techniques and thresholds used for the detection of arable lands are independently based on spectral characteristics and contrast properties of each image and are detailed in Annex 5.

2.5 Spatial modeling

2.5.1. General approach

The determination of potential water savings and the allocation of these savings to rainfed areas, discussed in sections 2.2 and 2.3, referred to individual pixels. GIS provides powerful functions for combining the necessary data layers and automating the calculations for all the pixels covering Syria. Despite such built-in capabilities in GIS software, it has been necessary to develop an algorithm and computer program for modeling the water allocation process.

All data processing and modeling has been done in raster mode. In the following sections the data layers used are described, as well as the different calculation steps.

The spatial modeling procedure is outlined in the flowchart of Fig. 9. The process starts with the compilation of climatic databases, satellite imagery and a digital elevation model for Syria. All these databases are converted into raster data layers that can be manipulated by different functions in GIS. From the climatic data layers new layers are derived that ultimately result in a layer of potential water savings (PWS). From the satellite imagery the land use/land cover layers are derived.

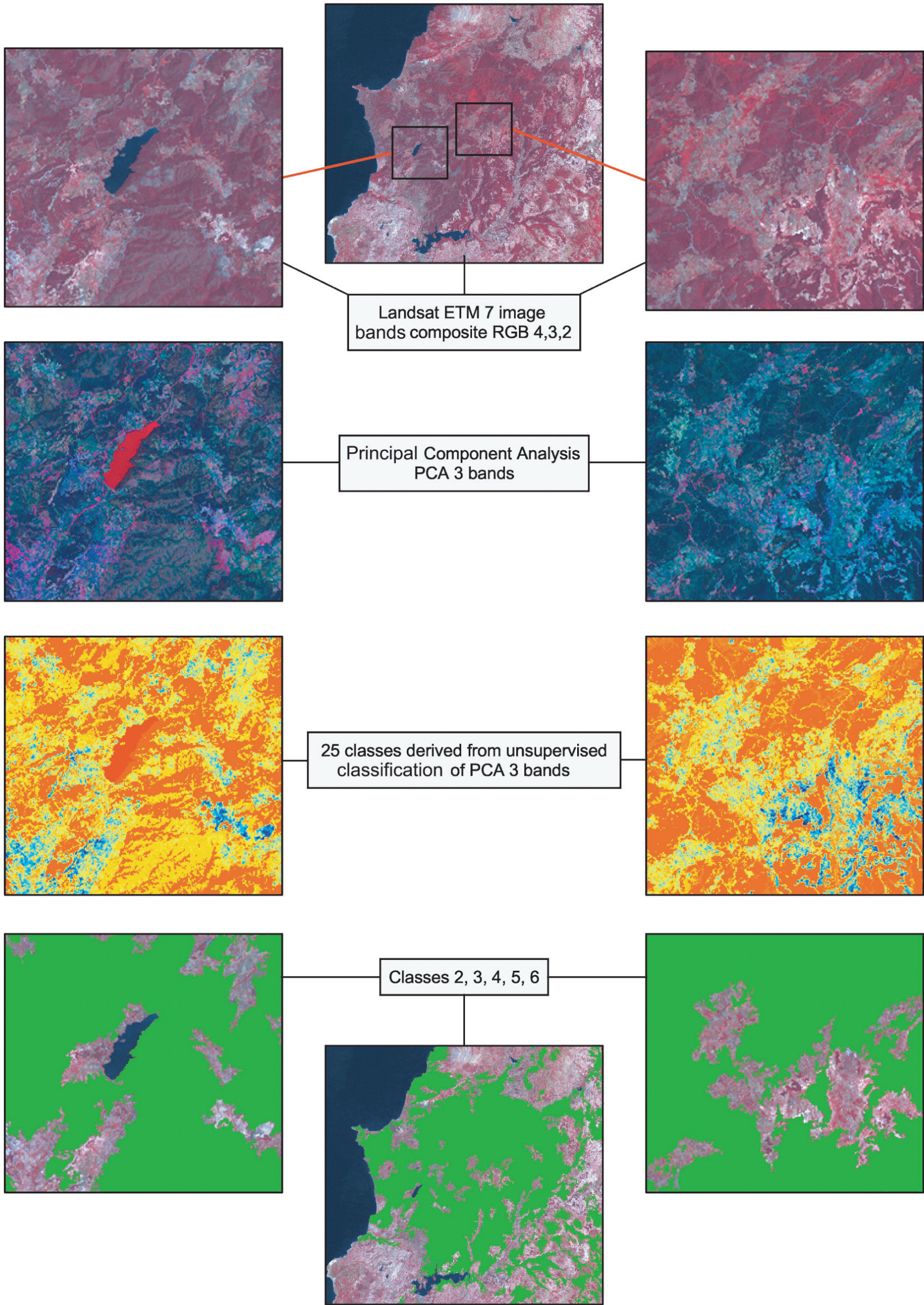


Figure 6. Use of PCA and unsupervised classification for mapping forest areas

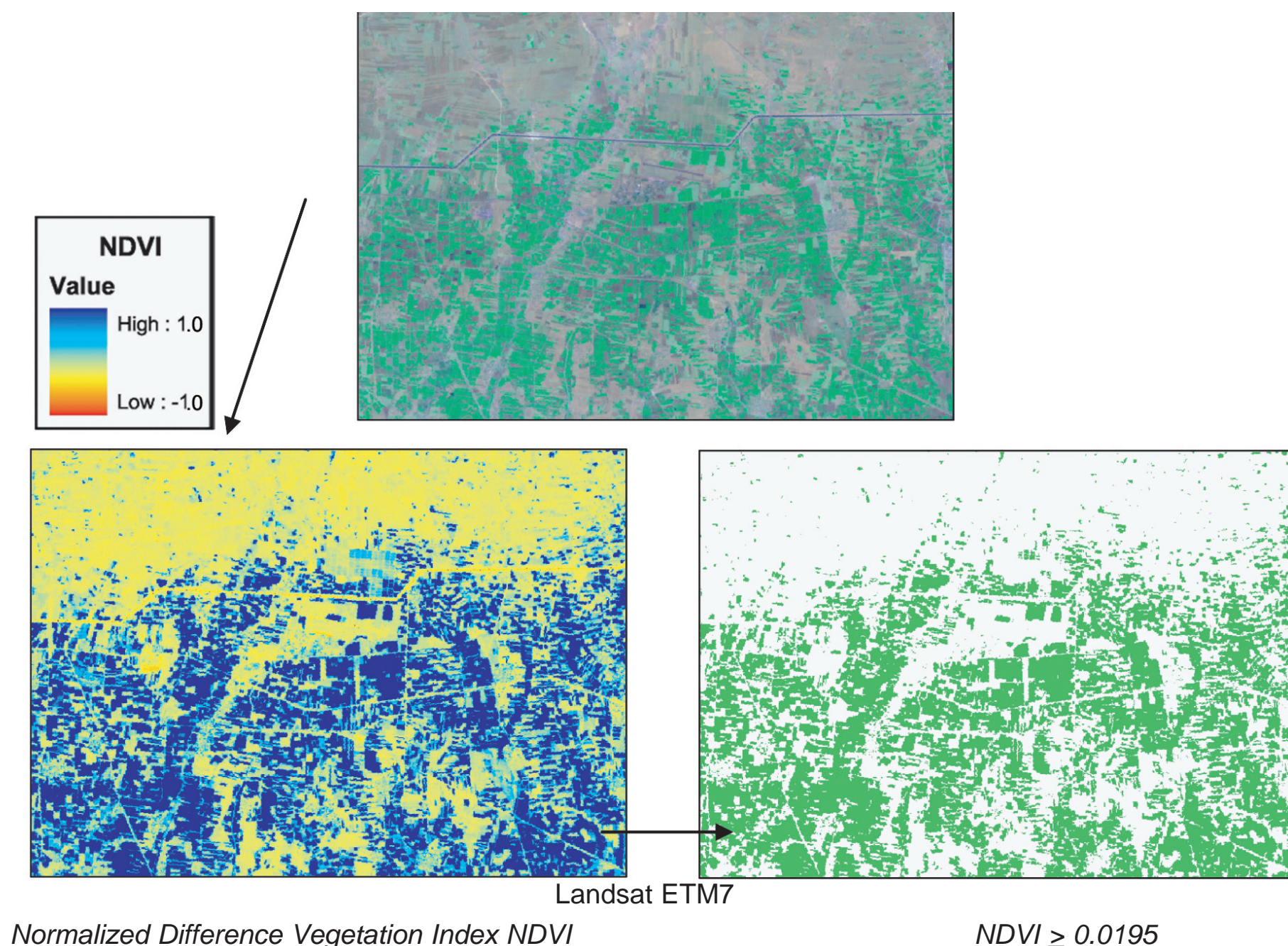


Figure 7. Use of NDVI threshold for extracting summer-irrigated areas

This is necessary for extracting the irrigated perimeters, distances from the irrigated perimeters, and identifying prohibited or potential areas for expansion of supplemental irrigation. From the digital elevation model, the permitted slope range is determined.

Finally suitability is assessed for all factors, resulting in layers of factor scores, which are combined by the method of the Most Limiting Factor (MLF) into a final suitability score, in the form of a 'allocation priority layer' (APL). The PWS and APL layers are then combined by means of the ***Spatial Water Allocation Algorithm*** (SWAA) to generate the layer of Pixel Water Allocations (PWA).

2.5.2. Input databases

Digital elevation model

The SRTM (Shuttle Radar Topographic Mission, see http://srtm.csi.cgiar.org/SRTM_FAQ.asp) is a high-resolution global digital elevation model (DEM), released in 2000. Its resolution is 3 arc-

seconds (90 m), suitable for use at scale 1:100,000. From this dataset, available from the Internet, the subset covering Syria was created and the slopes were derived using the *Slope* function in the Spatial Analyst module of ArcGIS. A slope map with three slope categories (0-5%, 5-20%, >20%) is provided on the CD accompanying this report (Map 1).

Climate

Mean monthly precipitation data were obtained for meteorological stations in and around Syria from the FAOCLIM2 database (FAO, 2001). Some of the potential evapotranspiration (PET-PM) data, calculated according to the Penman-Monteith method, were also obtained from the same source, also as monthly averages. For other stations monthly PET-PM was calculated from temperature data, obtained from the FAOCLIM2 database, using regression equations established between temperature, PET calculated by the Hargreaves method (PET-HG), and finally PET calculated by the Penman-Monteith method (De Pauw et al., 2004).

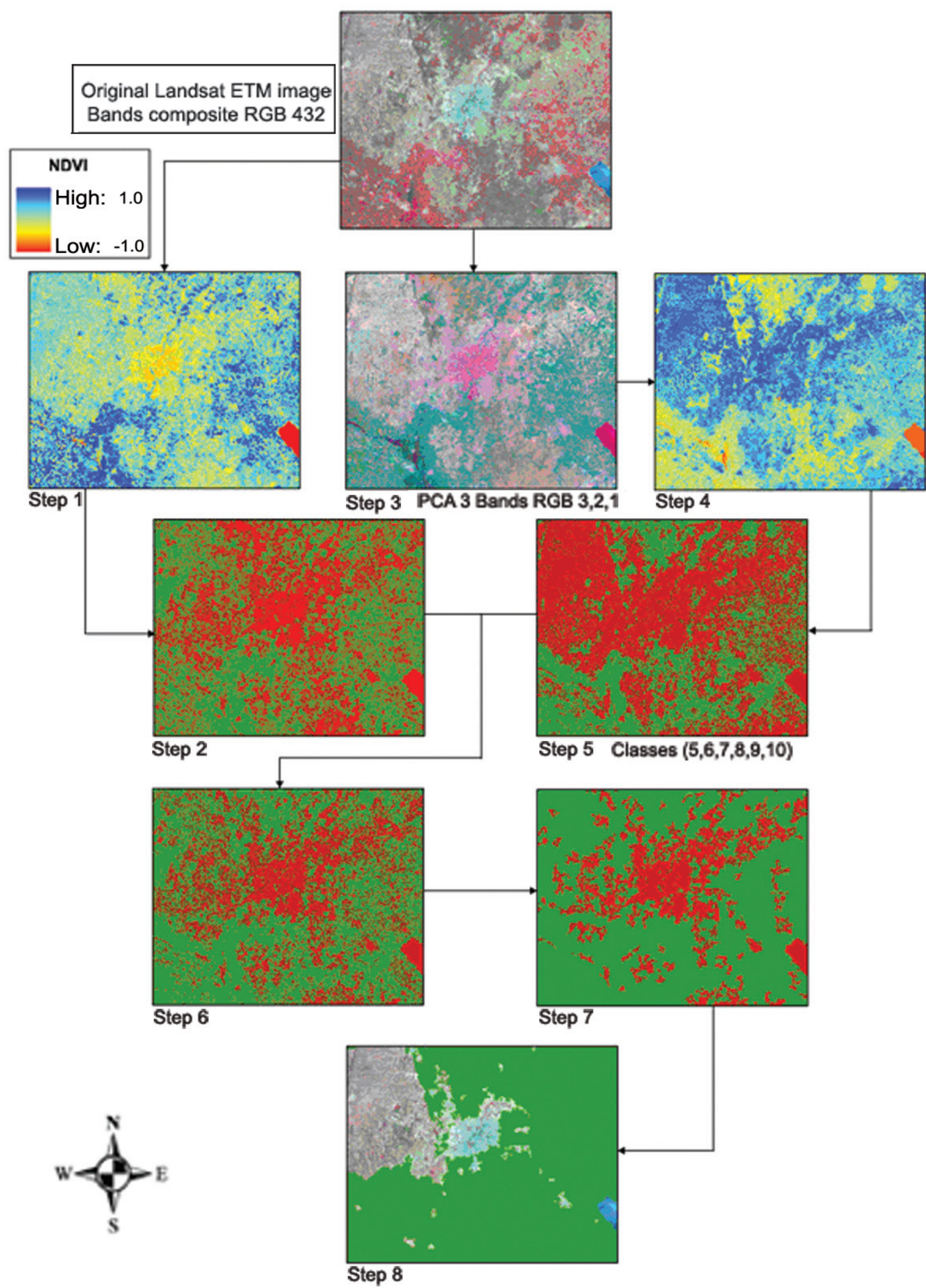


Figure 8. Processing steps used for the identification of arable land

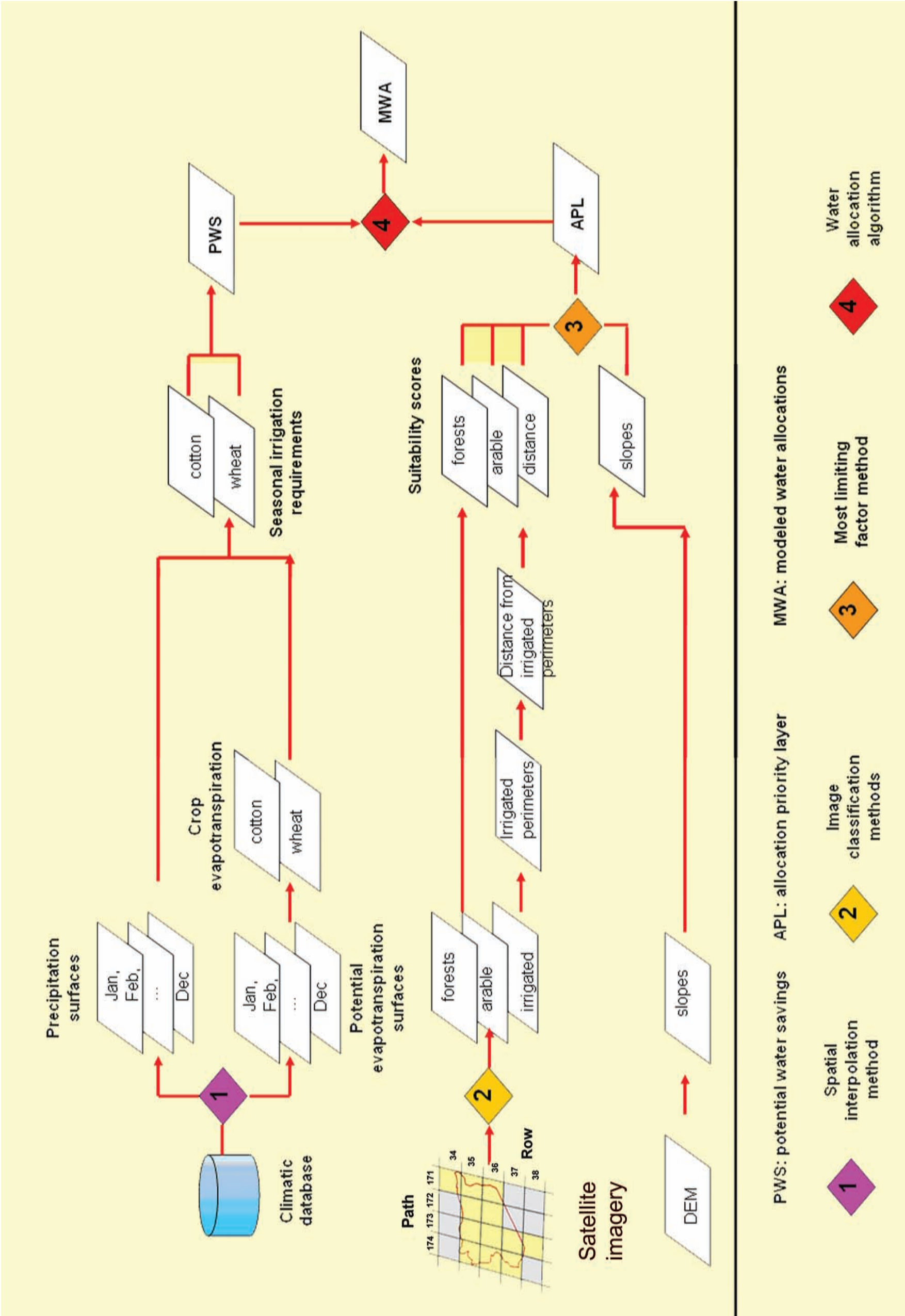


Figure 9. Flowchart of spatial modeling methodology

Spatial layers of mean monthly precipitation and PET-PM were then prepared from these point station data by spatial interpolation using the thin-plate smoothing spline method of Hutchinson (1995) and the ANUSPLIN interpolation software (Hutchinson, 2000). The monthly precipitation layers are provided on the CD as Maps 2-13, and the PET layers as Maps 14-25.

Satellite imagery

Landsat imagery was the basis for identifying areas irrigated in summer, forest areas and arable land by supervised classification methods, as outlined in section 2.4. The specifications of the imagery, pre-treatment and details of the supervised classification procedures for each of the layers are described in the same section and Annexes 3-5. The land use/land cover layers derived from the Landsat imagery are provided on the CD as Maps 26-28.

All input layers were standardized to the resolution of the SRTM digital elevation model, in order to combine them in raster mode.

2.5.3. Intermediate layers

Using the equations provided in section 2.2, the following derived climatic layers were created:

- crop evapotranspiration for cotton for the months April to September (Maps 29-34)
- crop evapotranspiration for wheat for the months November to May (Maps 35-41)
- total seasonal (April-September) irrigation requirement for cotton (Map 42)
- total seasonal (November-May) irrigation requirement for wheat (Map 43)
- potential water savings by shifting from cotton to wheat (Map 44)

In Maps 43 and 44, the western part of Syria as well as the most northeasterly tip has been masked as areas with sufficient precipitation to grow wheat. From the layer of irrigated areas (Map 26) a layer was prepared, using the *Distance Function* in the ArcGIS Spatial Analyst module, which shows the distance from irrigated areas (Map 45). In addition, a layer was prepared of the different irrigated perimeters, using the *Region Group* function in ArcGIS. Nearly 64,000 non-contiguous regions were identified. Of these, the ones covering less than 10 pixels (about 8 ha) were not retained for further processing.

Following the decision rules explained in section 2.3.2, four layers were prepared with scores (values 0-1) to assess suitability of individual pixels, with respect to the distance from irrigated areas (Map 46), slope (Map 47), absence of forests (Map 48), and presence of arable land (Map 49). The layer with the combined scores, or Allocation Priority Layer (APL), was prepared using the Most Limiting Factor principle (Map 50). A sample of the APL is shown in Fig. 10.

2.5.4. Allocating water savings

The allocation of water savings obtained by the shift from a fully irrigated crop to a partially irrigated crop is simple when considered only at the level of individual pixels. However, its implementation in GIS to cover an entire region or country demands a very complex calculation procedure. The reason is that there are many irrigated perimeters, each with their own neighborhood in which water transfers could occur, and that the neighborhoods overlap when irrigated perimeters occur close together, as is very often the case. For this reason a spatial water allocation algorithm (SWAA) was developed and implemented as a stand-alone Visual Basic program with built-in capabilities to recognize spatial objects and perform GIS functions. This section provides an overview of the SWAA. More details are provided in Annex 6.

Each irrigated perimeter was processed separately. Of the nearly 10,000 irrigated perimeters, only a subset of about 1650, containing those with a contiguous area of 48 pixels (40 ha) or more were processed. The reason is that processing each irrigated perimeter requires a very time consuming calculation. Including all 10,000 irrigated perimeters, while possible in theory, would have required at least 20 days continuous running on a very fast PC.

The exclusion of a number of irrigated perimeters from analysis was therefore dictated by the limit set by calculation time. When focusing on a much smaller area, there will be fewer irrigated perimeters to process and therefore no need to exclude on the basis of size.

The first step was to define a buffer zone around each irrigated perimeter. The buffer zone size indicates the total area in which it was

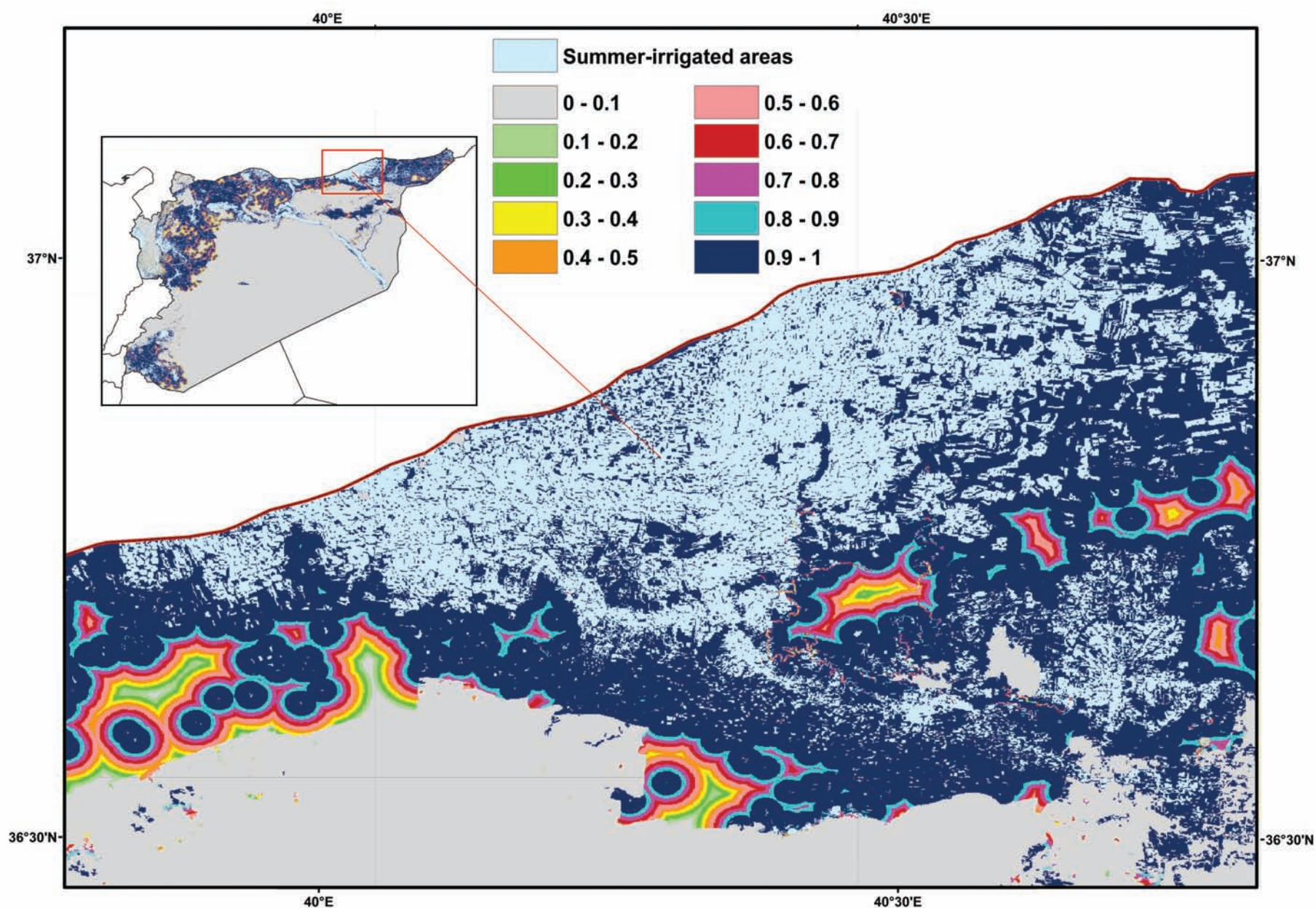


Figure 10. Modeled water allocation priorities for a sample area

assumed water transfers could occur, subject to other conditions being favorable. Pixels outside a buffer zone were assumed to be too far away from an irrigated perimeter and were therefore not processed.

The size of the buffer zone was assumed to vary with the size of the irrigated perimeter, to avoid expectations that water would be transferred very far from a very small irrigated area; realistically this would only be the case for large irrigated areas.

For this reason the buffer zone limits were tentatively set to a minimum, a maximum and intermediate values according to the size of the irrigated perimeter, with the following boundary conditions:

Min: 1 km for an area ≤ 50 pixels

Max: 5 km for an area ≥ 500 pixels

In between: a linear interpolation according to the formula

$$BZ = \frac{IPsize - LA}{UA - LA} * (UBZ - LBZ) + LBZ$$

where:

BZ: buffer zone

IPsize: size of the irrigated perimeter (in pixels)

LA: lower limit for area (here 50 pixels)

UA: upper limit for area (here 500 pixels)

LBZ: lower limit for buffer zone (here 1 km)

UBZ: upper limit for buffer zone (here 5 km)

The second step in the water allocation procedure was to combine the potential water savings (PWS) layer with the APL layer. Using GIS functions, allocation priority zones were created around *each* irrigated perimeter, on the basis of the scores against the suitability rules and their combination, as discussed in the previous section.

The underlying logic was that the more suitable a pixel from the perspective of the criteria used (slope, soil, forest and distance), the more likely that water diverted from the irrigated area would be used in that pixel.

The allocation priority scores have values in the range 0-1. The entire set of allocation priorities

was then split into 11 priority classes: 0, 0-0.1, 0.1-0.2, ...0.9-1. Starting with the top priority class, pixels were filled with an allocation equal to the precipitation-evapotranspiration deficit in that pixel. After each pixel fill, the total water savings stock (TWS) of an irrigated perimeter was reduced by the same amount. When the top priority class was filled, pixels in the next priority class were filled until the entire TWS was exhausted.

To avoid directional bias in the geographical positioning of the water allocations due to the direction of the pixel processing (west to east and north to south), the allocation process selected pixels within each priority class *at random*.

In cases that the TWS of an irrigated perimeter could not be depleted when all available pixels are processed (e.g. due to poor soils, topography or distance constraints), the ratio TWS_{end} / TWS_{start} or 'Usable Water Savings Ratio', indicates to what extent this condition exists. At the same time it answers the question what percentage of an irrigation scheme can potentially shift from full irrigation to supplemental irrigation. More on this is provided in the next section.

3. RESULTS

A first set of results can be found in file PWA_v2.XLS on the CD that accompanies this report. The file contains for each of the 1626 processed irrigated perimeters:

- TWS: the total water savings from the irrigated perimeter by shifting from cotton to wheat (column 4)
- Usable savings ratio: the percentage of the irrigated perimeter that can potentially shift from full irrigation to supplemental irrigation (column 7)
- The status of the potential water savings as related to potential needs in the surrounding area (column 8)

These results are summarized in Fig. 11 In over 70% of the irrigated perimeters, 80-100% of the potential water savings by shifting from cotton to wheat can be used in the surrounding areas,

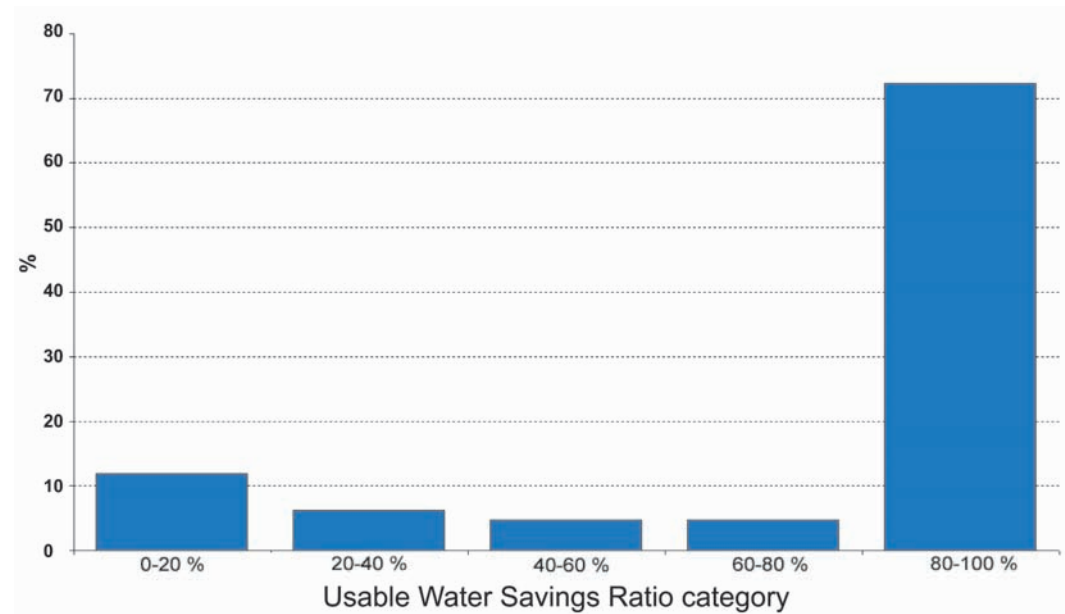


Figure 11. Percentages of irrigated perimeters within a usable water savings ratio category

taking into consideration the various limitations of distance, slopes, forests and arable land. This high figure already indicates that in most cases there are no major biophysical constraints in using saved water elsewhere. The histogram does not take into consideration about 50% of the processed irrigated perimeters, in which there is no need to irrigate because the precipitation is more than adequate to meet the water requirements of wheat. Nevertheless, about 12% of the irrigated perimeters have very low ratios of usable water savings (0-20%). This is mostly due to a proximity effect: where irrigated areas are very large and close together, the buffer zones overlap and therefore the saved water cannot be fully utilized.

The modeled water transfers from irrigated to rainfed areas with potential for supplemental irrigation are shown for the whole of Syria in Map 51. Areas with sufficient precipitation to grow wheat are masked in a bright green color. Areas in light grey color ('unprocessed pixels') are located in zones with rainfed agriculture, in which there is no potential for supplemental irrigation because there are no irrigated perimeters of sufficient size around which supplemental irrigation could develop. Areas in dark grey have no potential for supplemental irrigation, due to lack of irrigated perimeters, or because conditions are too dry for rainfed cultivation. Areas in rainbow colors have a potential for the introduction of supplemental irrigation. The colors indicate the amount (in mm) of irrigation water to be provided on top of local precipitation, to match the crop water requirements of wheat. Fig. 12 zooms into a sample area.

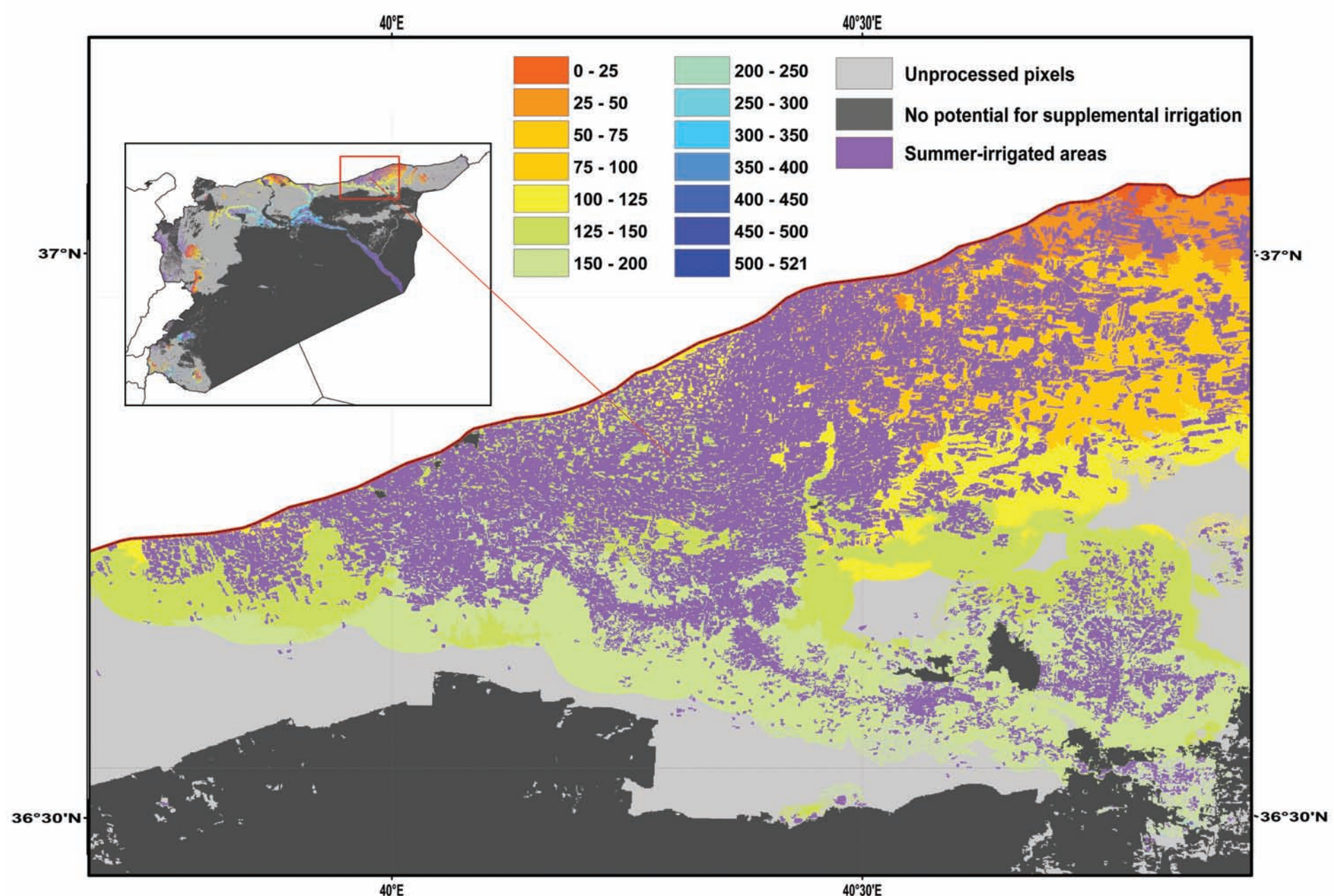


Figure 12. Modeled water allocations to rainfed areas, shown for a sample area

Table 4 summarizes the results of Map 51 in the form of area totals per administrative unit (province and district). The location of districts in Syria is shown in Fig.13 The areas in the third column do not represent the total area under irrigation, only the area with actively growing vegetation in summer at the time the satellite image was produced. Since fallow areas are not included, the figures are therefore underestimates of the areas under irrigation at one time or another.

The areas in the fourth column provide estimates of current areas under rainfed cultivation that could be converted to cultivation with supplemental irrigation. In some districts these areas are very low or even zero, e.g. Lattakia or Tartous province. These are administrative units where precipitation is normally sufficient not to necessitate supplemental irrigation, or where there is no land available for a shift from full to supplemental irrigation.

The next five columns indicate the percentage of each district that requires a certain level of water application (0-100 mm, 100-200 mm, 200-300 mm, 300-400 mm, 400-550 mm) to meet the crop water requirement of wheat.

The results of this modeling exercise suggest that Syria has a large potential for supplemental irrigation by shifting from a fully irrigated summer crop to a partially irrigated winter-spring crop. Roughly this potential amounts to a more than doubling of the area under irrigation. However, we must remember that this is a modeling exercise in which it has been assumed that all summer-irrigated crops will shift to winter-spring crops. This assumption is obviously unrealistic but was made to get a perspective on the potential impact of supplemental irrigation. Section 5 discusses how the impact of more complex changes in crop and water management patterns could be assessed through future research.

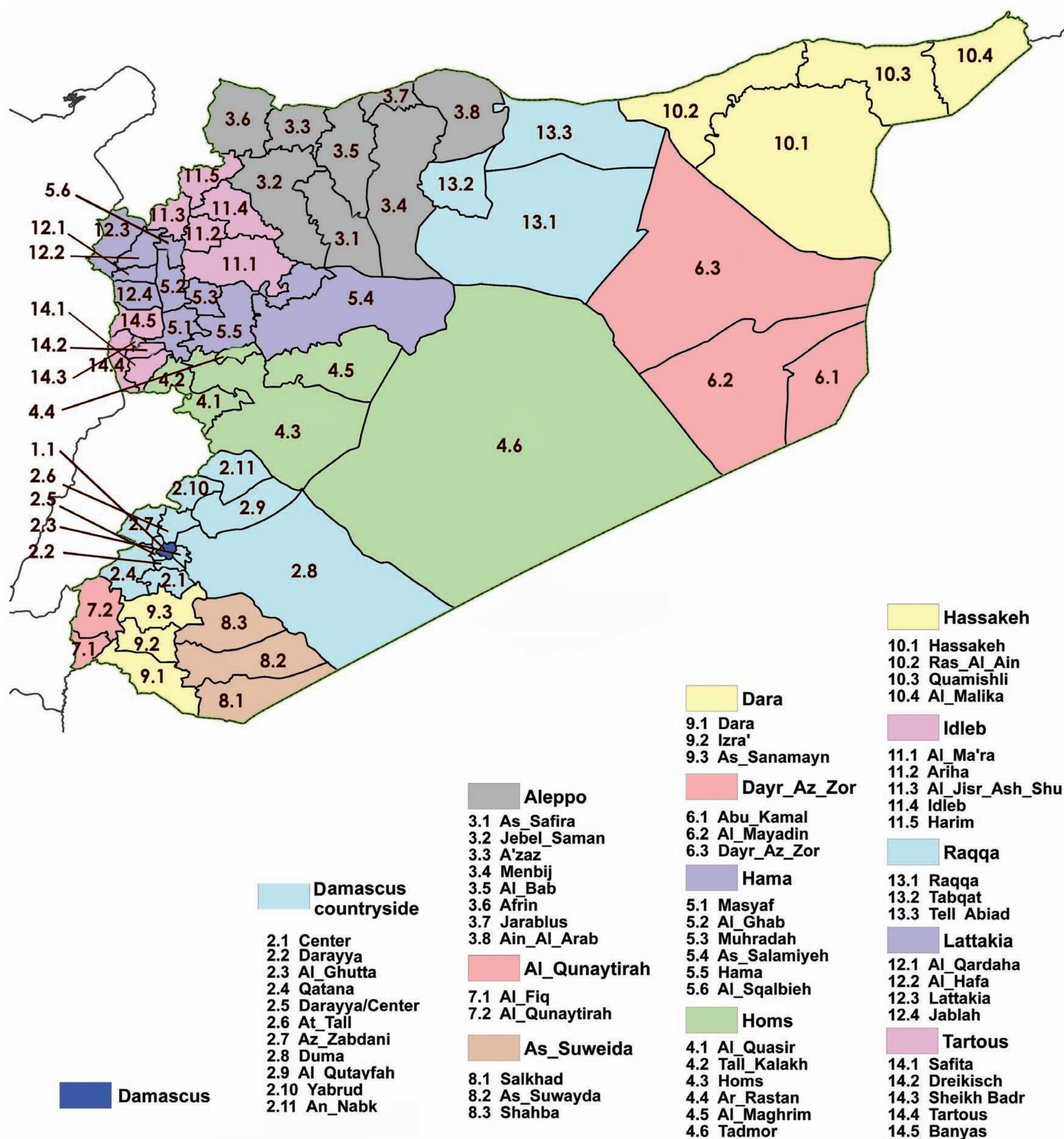


Figure 13. Districts of Syria

Table 4. Potential for supplemental irrigation in Syria by district

Montika	Currently irrigated (ha)	Potential supplemental irrigation (ha)	0-100mm %	100-200mm %	200-300mm %	300-400mm %	400-550mm %
Al Ghab Region							
Al Ghab	13,132	982	100	0	0	0	0
Al Sqalbieh	6,900	0	0	0	0	0	0
Mesiaf	7,037	0	0	0	0	0	0
Al Qunaytirah Province							
Al Fiq	4,563	13,485	66	20	13	1	0
Al Qunaytirah	9,331	5,235	70	30	1	0	0
Aleppo Province							
Afrin	5,438	1,396	100	0	0	0	0
Ain Al Arab	34,494	71,168	73	25	2	0	0
Al Bab	19,702	36,102	3	59	38	0	0
As Safira	16,735	27,990	0	78	22	0	0
A'zaz	2,881	6,564	100	0	0	0	0
Jarablus	2,608	13,231	26	74	0	0	0
Jebel Saman	17,843	53,496	5	94	1	0	0
Menbij	32,698	70,519	0	12	88	0	0
As Suweida Province							
As Suwayda	9,118	19,831	46	36	18	0	0
Salkhad	2,524	8,729	6	86	9	0	0
Shahba	72	434	33	66	1	0	0
Damascus Province							
City Damascus	1,019	4,390	0	0	68	32	0
Al Ghutta	8,024	2,494	0	0	0	100	0
Center	714	1,079	5	68	5	22	0
Darayya	2,054	4,661	0	0	56	44	0
Qatana	6,702	5,345	63	29	8	0	0
Damascus Countryside Province							
Al Qutayfah	436	133	7	0	66	27	0
An Nabk	174	490	100	0	0	0	0
At Tall	9	0	0	0	0	0	0
Az Zabdani	5,552	8	100	0	0	0	0
Darayya/Center	813	620	0	0	100	0	0
Duma	10,429	8,459	0	0	0	99	0
Yabrud	352	244	100	0	0	0	0
Dara Province							
As Sanamayn	971	335	0	29	71	0	0
Dara	14,656	19,489	3	35	58	4	0
Izra'	4,933	7,625	36	28	37	0	0
Dayr Az Zor Province							
Abu Kamal	25,582	20,124	0	0	0	0	100
Al Mayadin	21,626	15,011	0	0	0	0	100
Dayr Az Zor	41,555	33,211	0	0	0	55	45
Hama Province							
As Salamiyeh	232	1,170	0	100	0	0	0
Hama	8,345	22,727	27	72	0	0	0
Masyaf	7,829	4,257	100	0	0	0	0
Muhradah	14,197	31,087	96	4	0	0	0

Table 4. Continued

Hassakeh Province							
Al Malika	16,302	0	0	0	0	0	0
Hassakeh	51,407	116,681	3	95	2	0	0
Quamishli	33,909	84,125	90	10	0	0	0
Ras Al Ain	134,274	96,341	25	75	0	0	0
Homs Province							
Al Maghrim	44	0	0	0	0	0	0
Al Quasir	7,603	16,509	100	0	0	0	0
Ar Rastan	943	4,972	76	24	0	0	0
Homs	5,655	26,822	96	4	0	0	0
Tadmor	743	261	0	0	0	0	100
Tall Kalakh	4,133	0	0	0	0	0	0
Idleb Province							
Al Jisr Ash Shugur	4,209	0	0	0	0	0	0
Al Ma'ra	1,523	922	97	0	3	0	0
Ariha	289	0	0	0	0	0	0
Harim	2,523	0	0	0	0	0	0
Idleb	1,863	2,946	1	99	0	0	0
Lattakia Province							
Al Hafa	8,369	0	0	0	0	0	0
Al Qardaha	8,038	0	0	0	0	0	0
Jablah	16,079	0	0	0	0	0	0
Lattakia	24,484	0	0	0	0	0	0
Raqqa Province							
Raqqa	91,306	124,123	0	0	55	45	0
Tabqat	2,844	4,345	0	1	99	0	0
Tell Abiad	43,063	86,525	0	68	32	0	0
Tartous Province							
Banyas	5,980	0	0	0	0	0	0
Dreikisch	1,527	0	0	0	0	0	0
Safita	10,410	0	0	0	0	0	0
Sheikh Badr	199	0	0	0	0	0	0
Tartous	14,244	0	0	0	0	0	0
Total	853,239	1,076,695					

4. POTENTIAL FOR OUTSCALING

The methodology described in section 2 can be applied in other dryland areas without major modifications. It requires three sources of spatial data:

- DEM
- Climate surfaces
- Satellite imagery

The DEM is essential for deriving slopes, one of the key factors that determine the feasibility of supplemental irrigation. The resolution of the DEM is therefore important since low-resolution DEMs do not allow deriving slopes. A 30-m resolution DEM is optimal, although the SRTM DEM with 90 m resolution is still (but barely) acceptable.

Climate surfaces can be obtained from Internet databases (e.g. WORLDCLIM, see <http://www.worldclim.org/>). However, these datasets are at a low resolution (e.g. 1 km) which is insufficient for this method. A better way is to create oneself surfaces of precipitation and potential evapotranspiration. This requires access to a good local climatic database, e.g. from a national meteorological agency, and the use of an optimal spatial interpolation method, such as kriging or splining. In areas with topographic variations the interpolation method should make use of elevation, obtained from the DEM, as a third variable, in addition to latitude and longitude.

Landsat imagery is very suitable for obtaining the necessary land use/land cover classes that

are used in the evaluation. ASTER imagery (see <http://asterweb.jpl.nasa.gov/gettingdata/>), with 30 m resolution, is even better, but is not available at the same level of global coverage as Landsat. Strictly speaking, satellite imagery is not necessary if recent, good resolution land use/land cover maps are available. Several countries in Africa and Asia have fairly detailed land cover maps, generated through FAO's AfriCover and AsiaCover mapping projects. These vector maps, most of which are in the public domain, can be downloaded from a dedicated FAO website (http://www.africover.org/system/africover_data.php) and converted, after reclassification into raster layers. For this particular methodology, a minimum mapping scale of 1:100,000 is required.

Good soil maps can also make the interpretation of soil suitability easier. The use of satellite imagery to identify 'arable soils' as an indicator of suitability for supplemental irrigation is only if indeed all suitable land is already occupied for agricultural use. However, before rejecting image analysis to assess soil suitability, it is worth remembering that soil maps at appropriate scales (1:50,000 to 1:100,000) are in short supply in most countries, and that country-level overview maps are unsuitable for this methodology.

The factors, decision rules and thresholds that determine suitability and water allocation priorities can be adjusted to local conditions. The fuzzy function for slope range (Fig. 2) could, for example, be easily modified, or the distance rule. If good soil maps are available, different soil constraints could be introduced. The 'forest' category could be relaxed as a constraint, if different forest categories, with different biodiversity values, were identified.

5. FUTURE WORK

In this study the potential impact of supplemental irrigation, and its likely spatial distribution, are modeled through a single scenario: a 100% shift from one typical spring/summer crop, fully irrigated (cotton) to a typical winter/spring crop grown with supplemental irrigation when needed to meet the crop water requirements.

It is obviously unrealistic to consider this the only possibility and it should be clear that this study is a simplification of a much more complex reality. There are many irrigation schemes with different water management practices and expansion possibilities, crop options and ecological requirements.

In order to model these complex interactions, classical GIS work resulting in a collection of static maps (as on the enclosed CD) is not the answer. Instead, a GIS-based decision support system (DSS) is required. While such a DSS will be driven by the same methods and algorithms developed for this study, it will allow the user more control in developing relevant scenarios for change, which may differ from place to place.

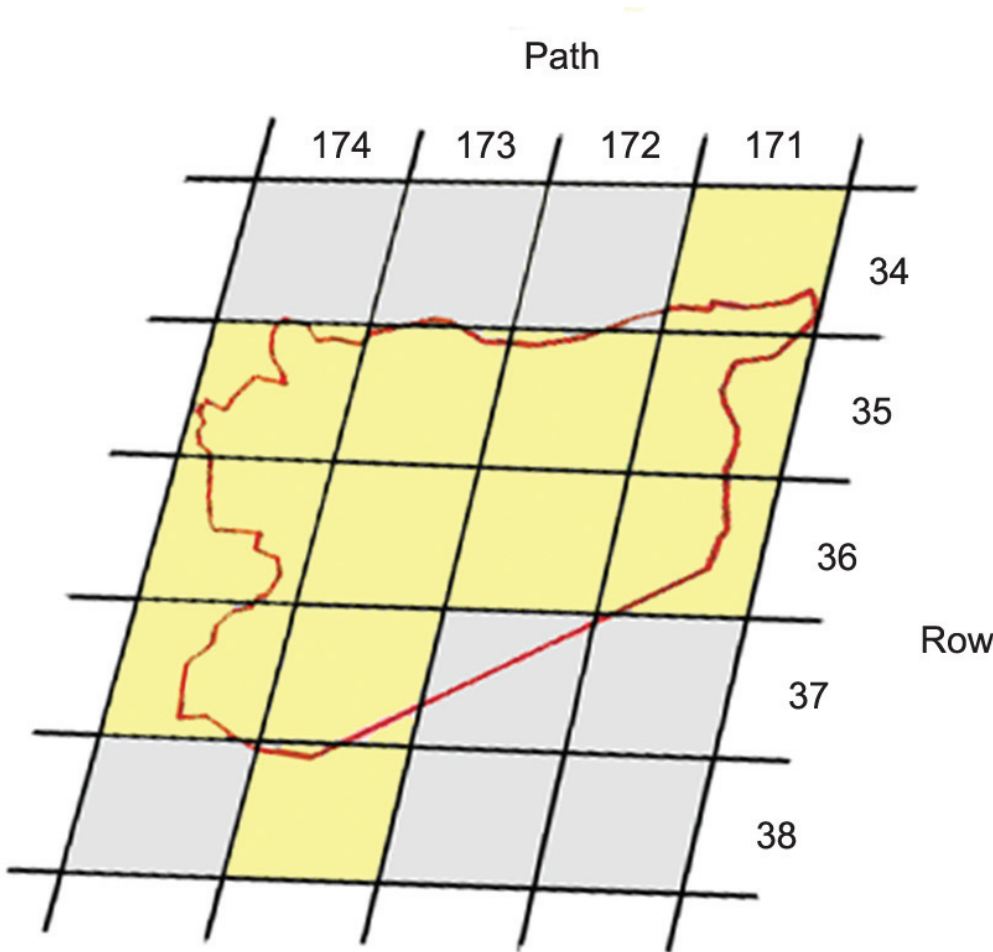
We are fully aware that development efforts into producing decision support systems can easily exceed their potential impact. It is therefore our intent to design the DSS as a very simple instrument for agricultural planners. It should obviously be easy to use, rely on robust and reliable data, and allow the user sufficient flexibility to change important parameters.

The vision for this DSS is that it will be an easily installable stand-alone software package with all components and databases included. These databases will need to be assembled for different countries or project areas. Although the DSS will have a simple GIS interface, it will not require the purchase of GIS software. Its interface will allow users to select an area inside a country (which could be a user-defined rectangle, an irrigation perimeter or a group of perimeters). It will allow users to specify the current and desired cropping patterns and water management techniques inside the selected area and change important parameters, such as the permitted slope range or distance from an irrigated area, and select prohibitive factors and their thresholds. The output will be in the form of dynamic maps and tables that will allow users to compare different scenarios.

REFERENCES

- Allen, R.G., L.S. Pereira, D. Raes and M. Smith. 1998. Crop evapotranspiration: guidelines for computing crop water requirements. FAO Irrigation and Drainage Paper 56, 300 pp., FAO, Rome.
- Cools, N., De Pauw, E. and Deckers, J. 2003. Integrating conventional land evaluation methods and farmers' soil suitability assessment: case of northwestern Syria. *Agriculture, Ecosystems and Environment* 95 (2003) 327-342.
- De Pauw, E., A. Ghaffari and V. Ghasemi. 2004. Agroclimatic zones map of Iran: explanatory notes. Research Report, Natural Resources Management Program, ICARDA, Aleppo, Syria, 44 pp.
- FAO. 2001. FAOCLIM 2. Worldwide agroclimatic database. CD ROM. FAO, Rome, Italy.
- Hutchinson, M.F. 1995. Interpolating mean rainfall using thin plate smoothing splines. *International Journal of Geographical Information Systems* 9: 385-403.
- Hutchinson, M.F. 2000. ANUSPLIN version 4.1. User Guide. Center for Resource and Environmental Studies, Australian National University, Canberra.
- Louis Berger International, Inc, Remote Sensing Institute South Dakota University, United States Agency for International Development and the Syrian Arab Republic. 1982. Land classification/soil survey project of the Syrian Arab Republic. Vol 2, Reconnaissance Soil Survey, 1:500,000 scale.
- Oweis, T., H. Zhang and M. Pala. 2000. Water use efficiency of rainfed and irrigated bread wheat in a Mediterranean environment. *Agronomy Journal* 92:231-238.
- Soil Survey Staff. 1975. Soil taxonomy: a basic system of soil classification for making and interpreting soil surveys. Soil Conservation Service, US Department of Agriculture, Agriculture Handbook No. 436.
- Sys, C., E. Van Ranst, J. Debaveye and F. Beernaert. 1993. Land evaluation. Part III. Crop requirements. ITC Agricultural Publications No. 7. Brussels, Belgium.
- Van de Steeg, J. and E. De Pauw. 2002. Overview of the soil resources of Syria. Research Report, Natural Resources Management Program, ICARDA, Aleppo, Syria.

Annex 1. Landsat imagery paths and rows



Annex 2. Landsat image processing for identification of water bodies

Image Path / Row	Technique used	Water bodies
174-035	<ul style="list-style-type: none">• PCA (3 bands)• Unsupervised classification (15 classes) to PCA 3	Classes 1, 4
174-036	<ul style="list-style-type: none">• PCA (3 bands)• Unsupervised classification (10 classes) to PCA 3	Classes 2, 3
174-037	<ul style="list-style-type: none">• Unsupervised classification (10 classes)	Class 1
173-035	<ul style="list-style-type: none">• PCA (3 bands)• Unsupervised classification (10 classes) to PCA 3	Class 1
173-036	<ul style="list-style-type: none">• PCA (3 bands)• Unsupervised classification (15 classes) to PCA 3	Class 1
173-037	<ul style="list-style-type: none">• Unsupervised classification (15 classes)	Classes 1, 4
172-035	<ul style="list-style-type: none">• PCA (3 bands)• Unsupervised classification (15 classes) to PCA 3	Class 3
172-036	<ul style="list-style-type: none">• PCA (3 bands)• Unsupervised classification (15 classes) to PCA 3	Class 1
171-034	<ul style="list-style-type: none">• PCA (3 bands)• Unsupervised classification (10 classes) to PCA 3	Class 1
171-035	<ul style="list-style-type: none">• PCA (3 bands)• Unsupervised classification (20 classes) to PCA 3	Class 1
171-036	<ul style="list-style-type: none">• Unsupervised classification (10 classes)	Class 1

Annex 3. LANDSAT image processing for identification of forest areas

Techniques used

1. *Remote Sensing*
 - Principal Component Analysis PCA (3 bands)
 - Unsupervised classification (25 classes) to PCA 3
2. *G/S*
 - Region group analysis
 - Exclude regionally grouped areas with less than 400 pixels
 - Visual interpretation

Image Path / Row	Results of classification using remote sensing
174 – 35	Forest areas: classes 2, 3, 4, 5, 6
174 – 36	Forest areas: classes 6, 7, 8, 9

Annex 4. LANDSAT image processing for identification of irrigated areas

Technique used

Normalized Difference Vegetation Index (NDVI), after excluding forest areas

Image Path / Row	Threshold
174 – 35	NDVI≥ 0.1
174 – 36	NDVI ≥ 0.1
174 – 37	NDVI ≥ 0.0195
173 – 35	NDVI ≥ 0.0195
173 – 36	NDVI≥0.0195
173 – 37	NDVI ≥ 0.0195
173 – 38	NDVI≥0.1875
172 – 35	NDVI ≥ 0.0195
172 – 36	NDVI ≥ 0.0195
171 – 34	NDVI ≥ 0.0195
171 – 35	NDVI ≥ 0.0195
171 – 36	NDVI ≥ 0.0443

Annex 5. LANDSAT image processing for identification of arable land

Techniques used:

The image analysis included:

- Unsupervised classification of either all bands or the three bands obtained by principal component analysis (PCA)
- Selection of the classes that best represent arable land by comparison with visual image
- Setting minimum thresholds for NDVI to qualify as 'arable land'

In all cases NDVI thresholds were set to a minimum of 0.01, except in location 173-35, where the limit was 0.02. The location-specific image processing steps are summarized in the table below.

Image analysis was followed by region group analysis in order to reduce the fragmentation of the selected classes. In all images groups consisting of less than 100 pixels of the selected classes were dissolved into the other classes, whereas groups smaller than 1000 pixels of non-selected classes were dissolved into the selected classes.

Finally, some manual revisions were made on the basis of visual interpretation. In locations 174-35 and 174-36 areas positively identified as 'forests' were masked.

Path/row	PCA	Number of classes	Selected classes
174-35	Yes	15	5, 6, 7, 8, 9, 10
174-36	Yes	10	4, 5, 8, 9, 10
174-37	No	25	7, 8, 9, 10, 18, 21
173-35	Yes	10	4, 5, 6
173-36	No	None	NDVI used only
173-37	No	25	2
173-38	No	10	2, 3, 4, 5
172-35	Yes	15	1, 4, 5, 7
172-36	Yes	15	3
171-34	Yes	10	2, 3, 4, 5, 6, 7, 8
171-35	Yes	15	1, 3, 4, 5
171-36	Yes	15	3, 5

Annex 6. Spatial Water Allocation Algorithm

Introduction

The theoretical basis for this algorithm is explained in Chapter 2. In order to situate the various steps used by the algorithm, a short summary is provided.

Allocation Priority Layers (APLs) are created for each irrigated perimeter. Priorities for allocation of available water to a particular pixel are based on the degree of compliance with rules for suitable slopes, soils, distance, and absence of forests, emulating the logic that the more the pixel complies with the rules, the more likely that water diverted from the irrigated area will be used in that pixel.

The entire set of allocation priorities (with values in the range 0-1) is split into 11 priority classes: 0, 0-0.1, 0.1-0.2, ...0.9-1. Starting with the top priority class, pixels are filled with an allocation PWA equal to the precipitation-evapotranspiration deficit. At each pixel fill, the water savings stock TWS is reduced by the same amount. When the top priority class is filled, pixels in the next priority class are filled until the entire TWS is exhausted.

To emulate the essentially random distribution of fields shifting from rainfed to irrigated agriculture, the allocation process selects pixels within each priority class *at random*.

Approach

It is impossible to implement an algorithm that executes the steps outlined above by processing individual pixels, due to memory limitations. Instead, the procedures make use of Zonal Statistics functions, only available in GIS, which allow working with ranges of pixels instead of pixel-by-pixel. In this approach the program iteratively creates a grid of pixels that meet the condition $PWA \leq TWS$, where:

TWS: is the total potential water savings (PWS) within each irrigated perimeter (IP)

PWA: is the total of $Etc_{irr,wheat}$ outside the IP with the accordance with APL.

Steps

1. Load the required grids into computer memory. Sort the *IPs* in descending order and create a table (***IP-table***) containing the IP IDs, the number of pixels in each IP and three fields to accommodate the values of TWS, initial PWA and the final PWA
2. Initialize an iteration loop over all IPs. Create for each IP a grid layer containing only the IP under processing; assign to the other IPs the value 'No Data'. The output grid is given the name ***IPZone***.
3. Obtain the *PWS* for the particular *IPZone*. The name of the resultant layer is ***PWS_IPZone***.
4. Calculate the ***TWS*** for the particular *IPZone* using the zonal statistics 'ZonalSum' function on the *PWS_IPZone* grid. Write the *TWS* to the relevant record in the *IP-table*.
5. Define the ***processed area*** as the area that surrounds the *IPZone* (distance >0 m) and does not exceed 5000 m, using the *Euclidian Distance function* (***EucDistance***). The output layer is ***IP_Dist***.
6. Check the possibility that the processed area exists. In some cases, there are no arable lands surrounding the IP and all the pixels around them are assigned 'No Data'. In such cases the intersection of the APL with the processed area results in a grid containing only 'No Data' values.
7. Check if the processed area contains flagged pixels. Flagged pixels are pixels that have been processed in previous loops. Flagged pixels are taken out from the processed area.
8. Overlay the *IP_Dist* with the ***Etc_{irr,wheat}*** to create an *Etc_{irr,wheat}* layer bounded by the *IP_Dist*. The output layer is named ***PWA_IPDist***.
9. Calculate the sum of *Etc_{irr,wheat}* in *PWA_IPDist* using the zonal statistics 'ZonalSum' function. The value returned ***PWA01*** is written into the *PWA-initial field* of the relevant record in the *IP-table*.
10. Compare *PWA01* with *TWS*. If $TWS \geq PWA01$, the entire processed area is filled up and the iteration processes the next IP. The remaining steps (11-12) of the algorithm are

omitted and the iteration returns to step 2. If $TWS < PWA01$ the program enters a new iteration (step 11).

11. From this stage onward the APL plays the most important role in the calculation. The processed APL output layer (**APL_IPDist**), containing allocation priorities within the buffer zone, is created by overlaying the APL layer, calculated using the suitability rules in section 2.3.2, with the *IP_Dist* layer.
12. To speed up the calculation and to avoid the redundancy of merging many narrower classes ('slices') to form the final PWA grid (**PWA_Grid**), loop over the priorities ranges in the *APL_IPDist* considering the following ranges: 0.1-1, 0.2-1, 0.3-1, 0.4-1, 0-1, 0.6-1, 0.7-1, 0-1, and 0.9-1. Since $TWS < PWA01$, the range (0-1) which represents the entire processed area is omitted.
 - 12.1. Isolate the area that covers the specific range, starting from the widest range (0.1-1). The name of the output grid is **APL_Class**.
 - 12.2. Create a mask from *APL_Class* and overlay it over *Etc_{irr,wheat}*. Name the output grid **PWA_APL_Class**.
 - 12.3. Use the 'ZonalSum' function to calculate the sum of *Etc_{irr,wheat}* within the *APL_Class* zone (**Sum_PWA**).
 - 12.4. Compare *Sum_PWA* with *TWS*. If $TWS < Sum_PWA$, loop over the next (narrower) range. The iteration is repeated until the condition $TWS \geq Sum_PWA$ becomes true. At that time, the program exits the loop, keeps the last resultant grid to be added to the final *PWA_Grid* and moves to the next steps. The main objective of this stage is to select some pixels from the lower priority slice and add them to the selected range to make the difference between *TWS* and *Sum_PWA* as small as possible. For example, if the condition $TWS < Sum_PWA$ is true at the range (0.5-1), the program will select some pixels from the slice (0.4-0.5) to make the *TWS* either equal to or slightly greater than *Sum_PWA*.
 - 12.4.1. Create a grid layer from the lower slice (e.g. 0.4-0.5) and name the grid **APL_Class01**. Overlay *APL_Class01* and *Etc_{irr,wheat}* and name the resultant grid **PWA_APL_Class01**. Calculate the sum of the values in *PWA_APL_Class01* and

name the new value **Sum_PWA01**. Add *Sum_PWA01* to *Sum_PWA* to create **Sum_PWA02**, which is $> TWS$.

12.4.2. Convert the *APL_Class01* grid to a point feature class shape file. The objective of this step is to calculate the number of *unique* values in the floating point grid data type.

12.4.3. From the point feature class, take the number of rows and name it

NumOfRows.

12.4.4. If $NumOfRows \leq 2000$

12.4.4.1. Get the attribute table of *PWA_APL_Class01*.

12.4.4.2. Sort this table in ascending order.

12.4.4.3. Get into a new iteration loop (**Loop03**) covering the table's rows.

12.4.4.4. Read the *Etc_{irr,wheat}* (**PWAVal**) and the count (**CountVal**) value for each row.

12.4.4.5. Multiply the two values to form the product $PWAVal01 = PWAVal * CountVal$

12.4.4.6. Subtract *PWAVal01* from *SumPWA02*. $SumPWA02_{new} = SumPWA02_{old} - PWAVal01$.

12.4.4.7. Compare *SumPWA02_{new}* with *TWS*.

12.4.4.8. Terminate the iteration process if $SumPWA02 < TWS$. The value of *PWAVal* still in the computer memory, represents the lowest value that meets the condition $SumPWA02 < TWS$ and is used in the next step.

12.4.4.9. Create a new grid layer that meets the condition $[PWA_APL_Class01 \geq PWAVal]$ (raster logical operation). Name this grid **PWA_APL_Class02**.

12.4.4.10. Create the final PWA grid layer (**PWA_Grid**), from the sum of the layers *PWA_APL_Class* and *PWA_APL_Class02* and write the value of the final PWA to the table in the field *PWA_final*.

12.4.4.11. Create the Flag Grid layer under the name **Flag_Grid**.

12.4.4.12. Go to step 1.

12.4.5. If $NumOfRows > 2000$

12.4.5.1. Convert the *APL_Class01* to a point feature class. The resultant point shape file contains an important field (**POINTID**) which contains unique IDs for

the unique values in the floating point data type.

12.4.5.2. Convert the point shape file into a grid using the POINTID field. Each cell in the resultant grid has a unique ID. Name the ID grid **Ids_Grid**.

12.4.5.3. Divide the **NumOfRows** by 2000 to obtain the number of repeatable operations (N); $N = \text{Int}(\text{NumOfRecs} / 2000)$.

12.4.5.4. Repeat the creation of zones consisting of 2000 pixels by using a loop starting from 1 to N.

12.4.5.5. Isolate each zone grid using the formula $\text{Ids_Grid} > \text{Counter} * 2000$. Make the resultant grid a mask and create a zone from **PWA_APL_Class01**. Name the new grid **PWA_APL_Class02**. Calculate the sum of the pixel values using the ZonalSum function and name the output grid **Sum_PWA01**.

12.4.5.6. Calculate the grid **Sum_PWA02** as the sum of **Sum_PWA** and **Sum_PWA01**.

12.4.5.7. Compare **Sum_PWA02** with **TWS**. If $\text{Sum_PWA02} < \text{TWS}$ then terminate the looping process and go to the next step. Else, go to the next counter.

12.4.5.8. Start a new processing block similar to the block 12.4.4. The main aim of this step is to select some other pixels from the lower slice $\{\text{Counter} * 2000 - (\text{counter} - 1) * 2000\}$, and add them to the grid layer selected in the previous step (12.4.5.7.).

The outcome from that block is a new grid layer with the name **PWA_APL_Class04**.

12.4.5.9. **PWA_Grid** is created as the sum of the three grids **PWA_APL_Class**, **PWA_APL_Class02** and **PWA_APL_Class04**.

12.4.5.10. Create the **Flag_Grid** and write the final value of **PWA** to the table.

12.4.5.11. Go to step 2, select next IP.

12.5. If the program encounters the condition $\text{TWS} < \text{Sum_PWA}$ while the iteration process reaches the highest priority range (0.9-1), some pixels must be selected from within the highest class. The treatment of this case is similar to the case in which $\text{TWS} \geq \text{Sum_PWA}$ but where the iteration does not reach the highest class. In this stage some pixels have to be assigned in a random distribution that meets the condition $\text{TWS} \geq \text{Sum_PWA}$. This can be achieved by the following steps:

12.5.1. Use the 'Rand' function in the ArcGIS Spatial Analyst to create a randomized grid layer in accordance with the **APL_Class** layer produced in the stage 12.4. 'Rand' generates a grid of random numbers between '0' and '1'. That enables the program to iterate over ranges similar to the ones of priorities in section 12.4. The advantage of this approach is that the randomization can be combined with the zonal statistics.

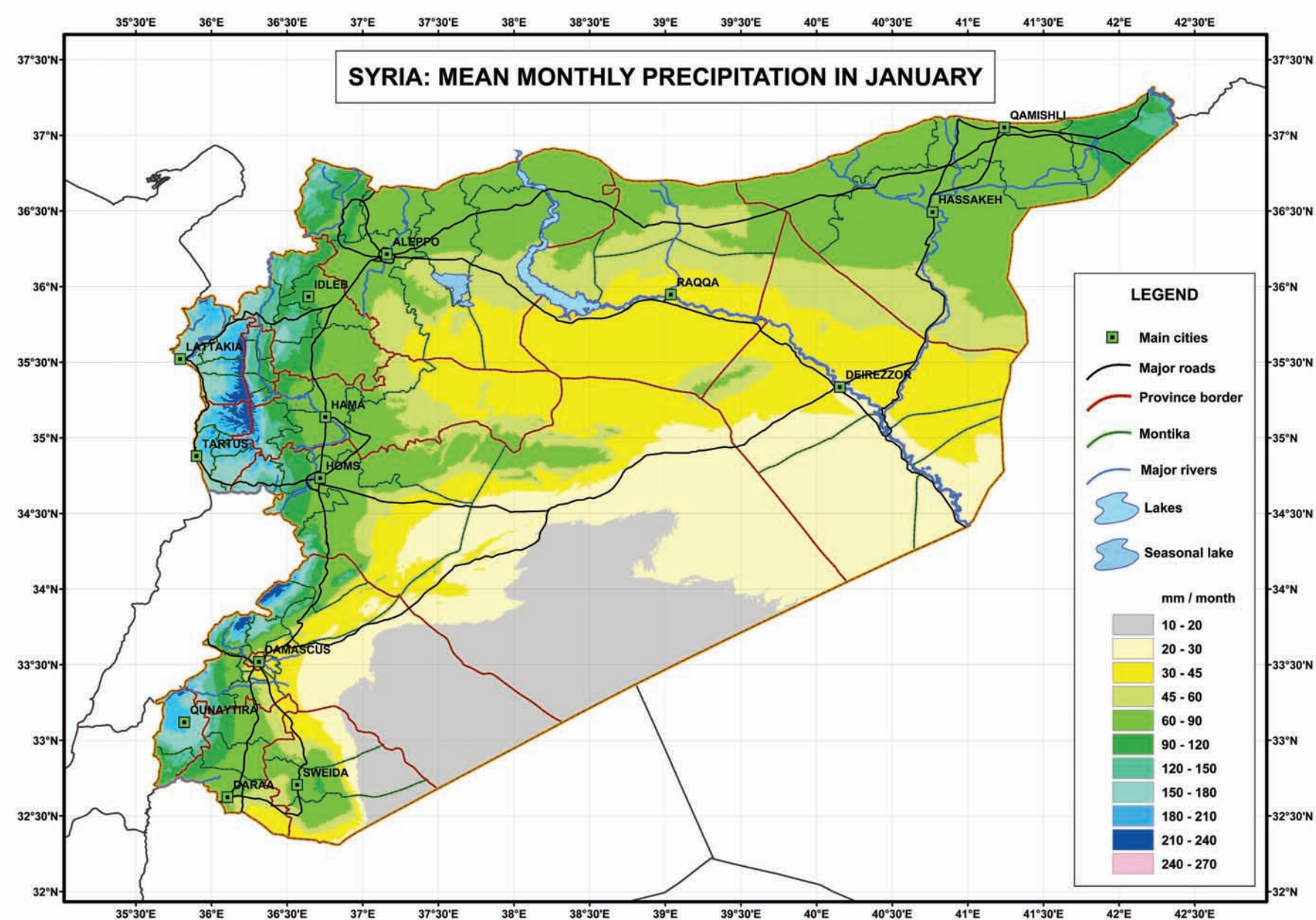
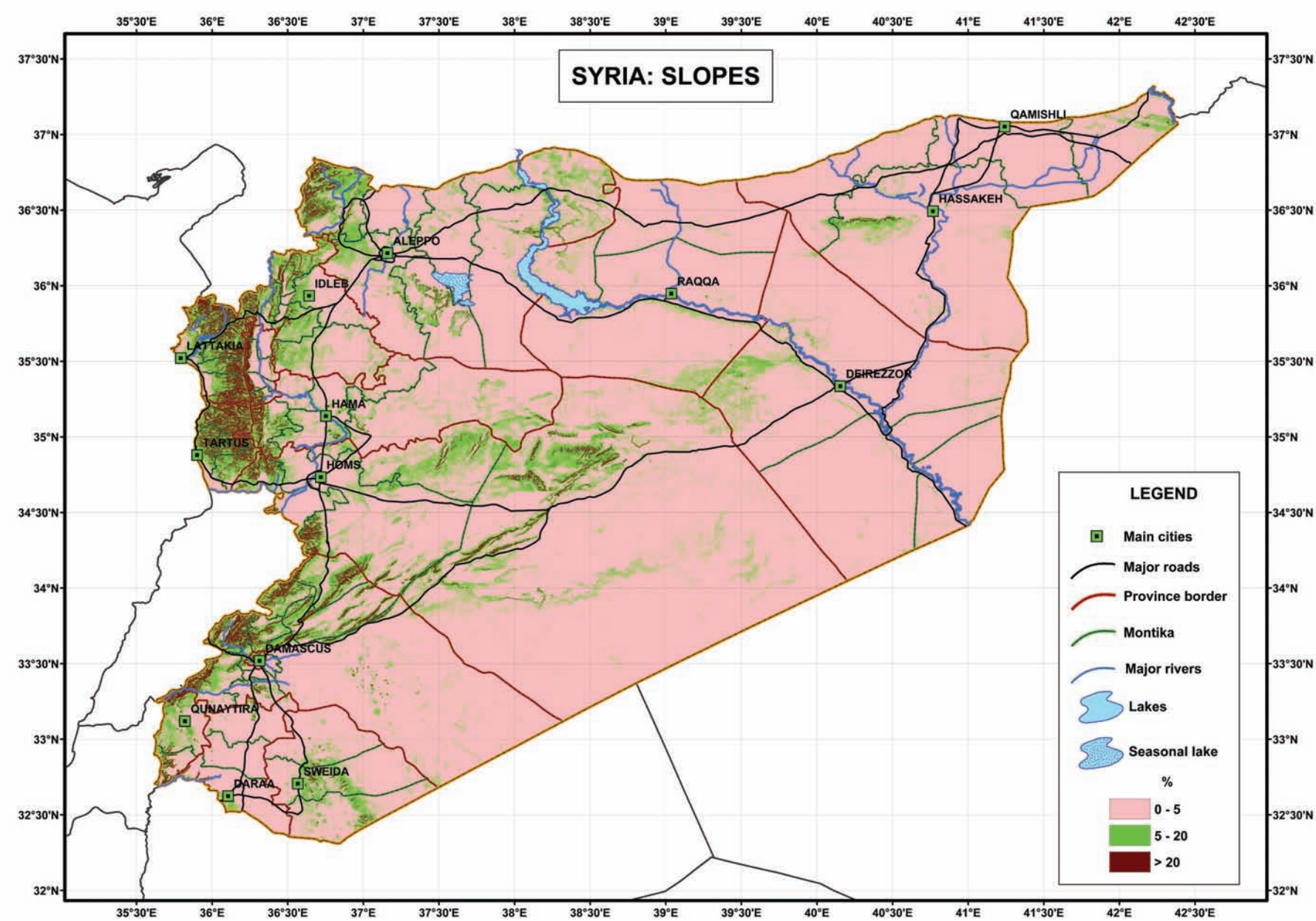
12.5.2. The remaining steps are the same as steps 12.4.1 to 12.4.6.11. In this case the **PWA_Grid** is formed from 2 grids if $\text{NumOfRows} \leq 2000$, and formed from 3 grids if $\text{NumOfRows} > 2000$.

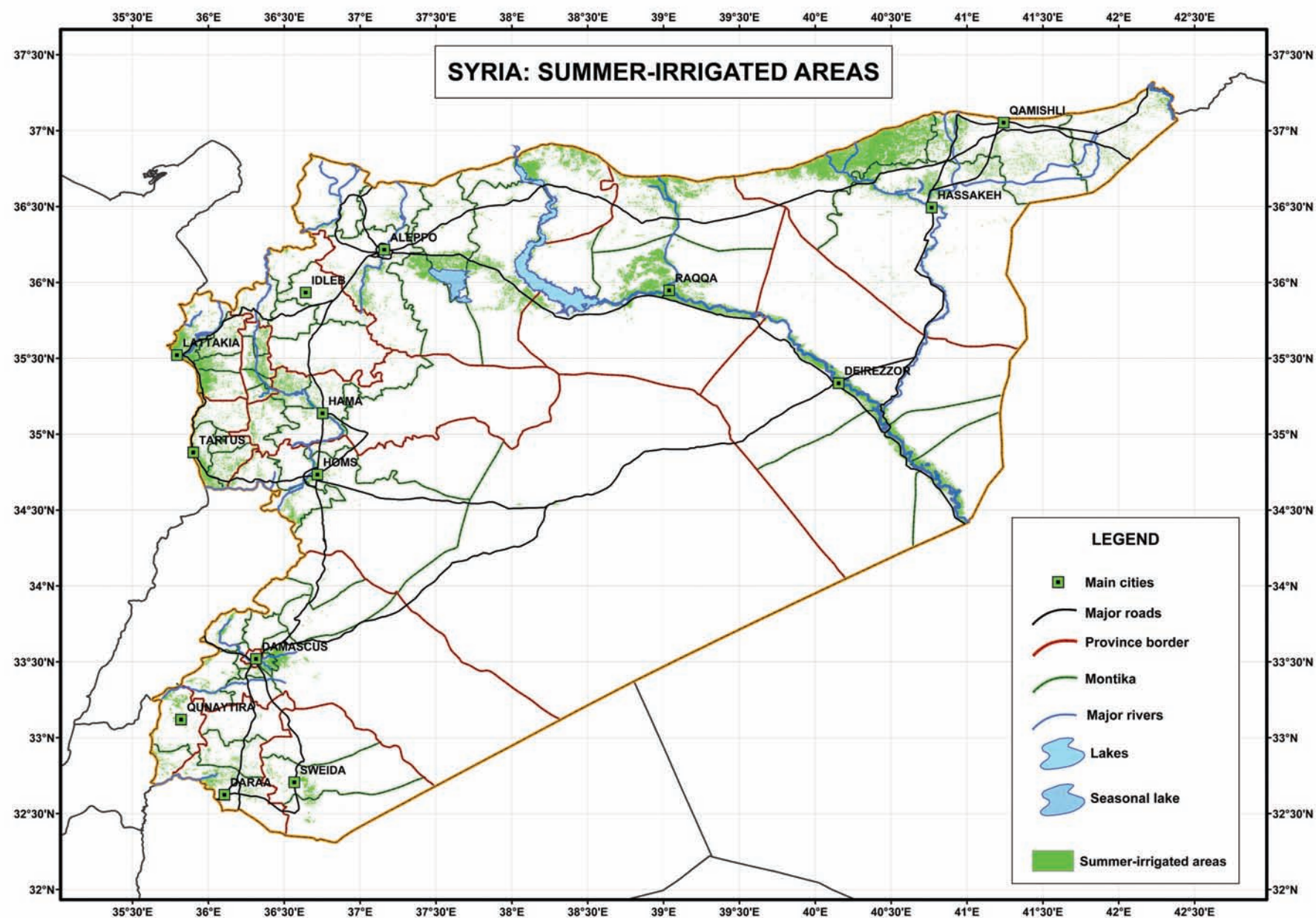
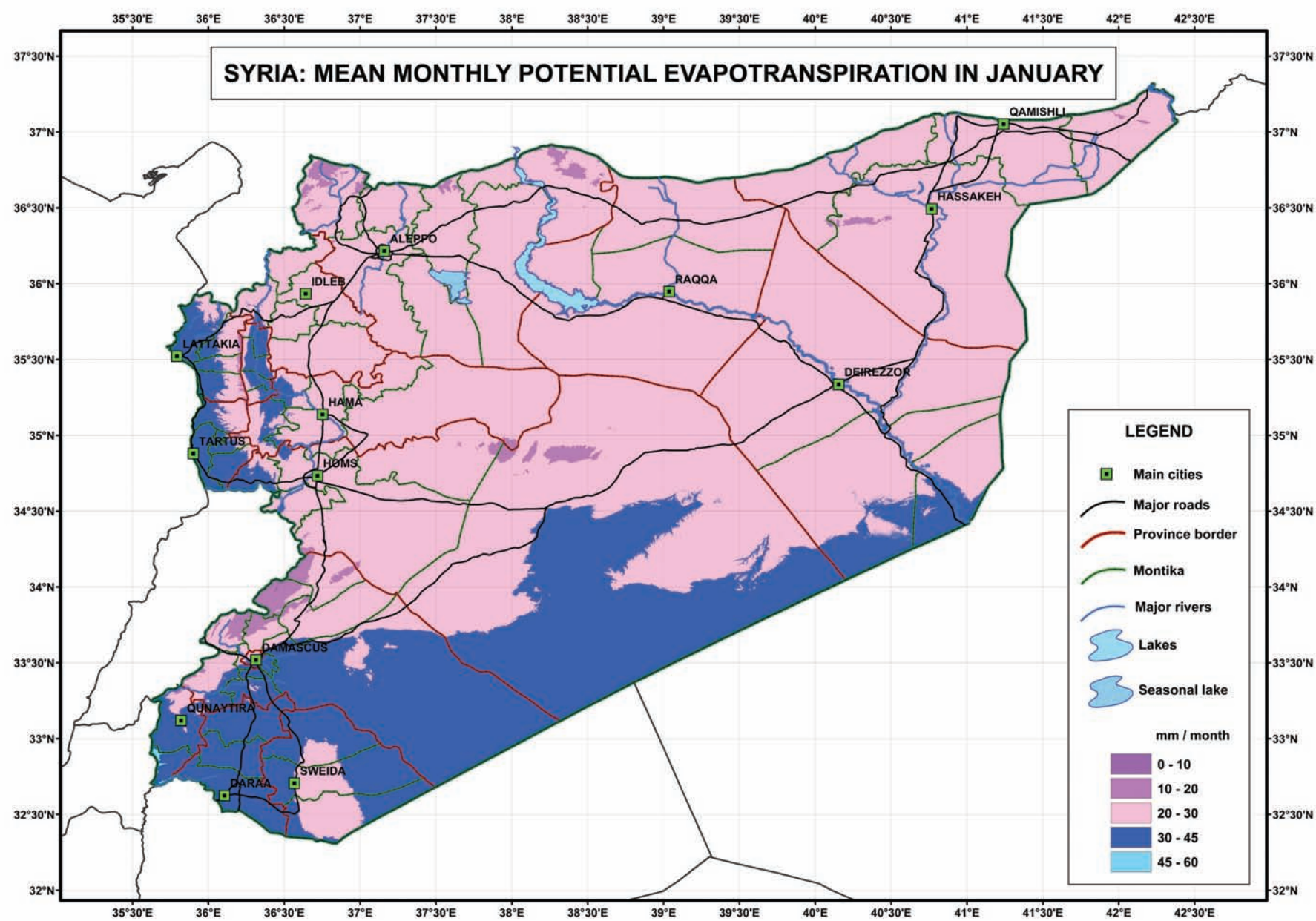
13. Within the same loop the program saves the **PWA_Grid** and the **Flag_Grid** files to disk after the final values have been entered, in order to save the data in case of an unexpected computer problem. In addition, the program deletes the **PWA_Grid** and **Flag_Grid** files from earlier iterations to avoid a space crunch on the hard disk. Also, the program is provided with procedures to delete the temporary folder from the grids created during the calculation processes. When the program reaches the last IP, the final **PWA_Grid** is created.

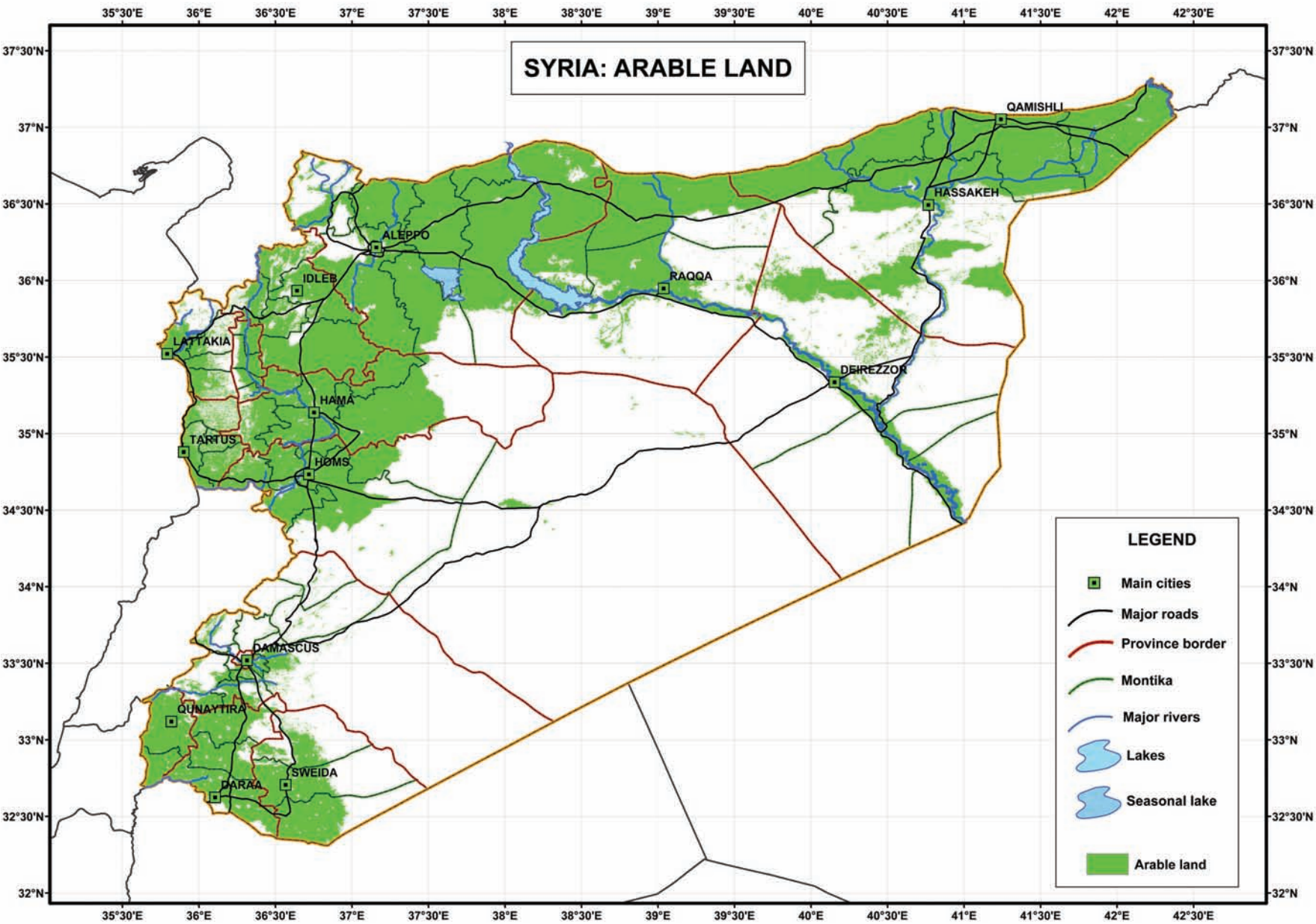
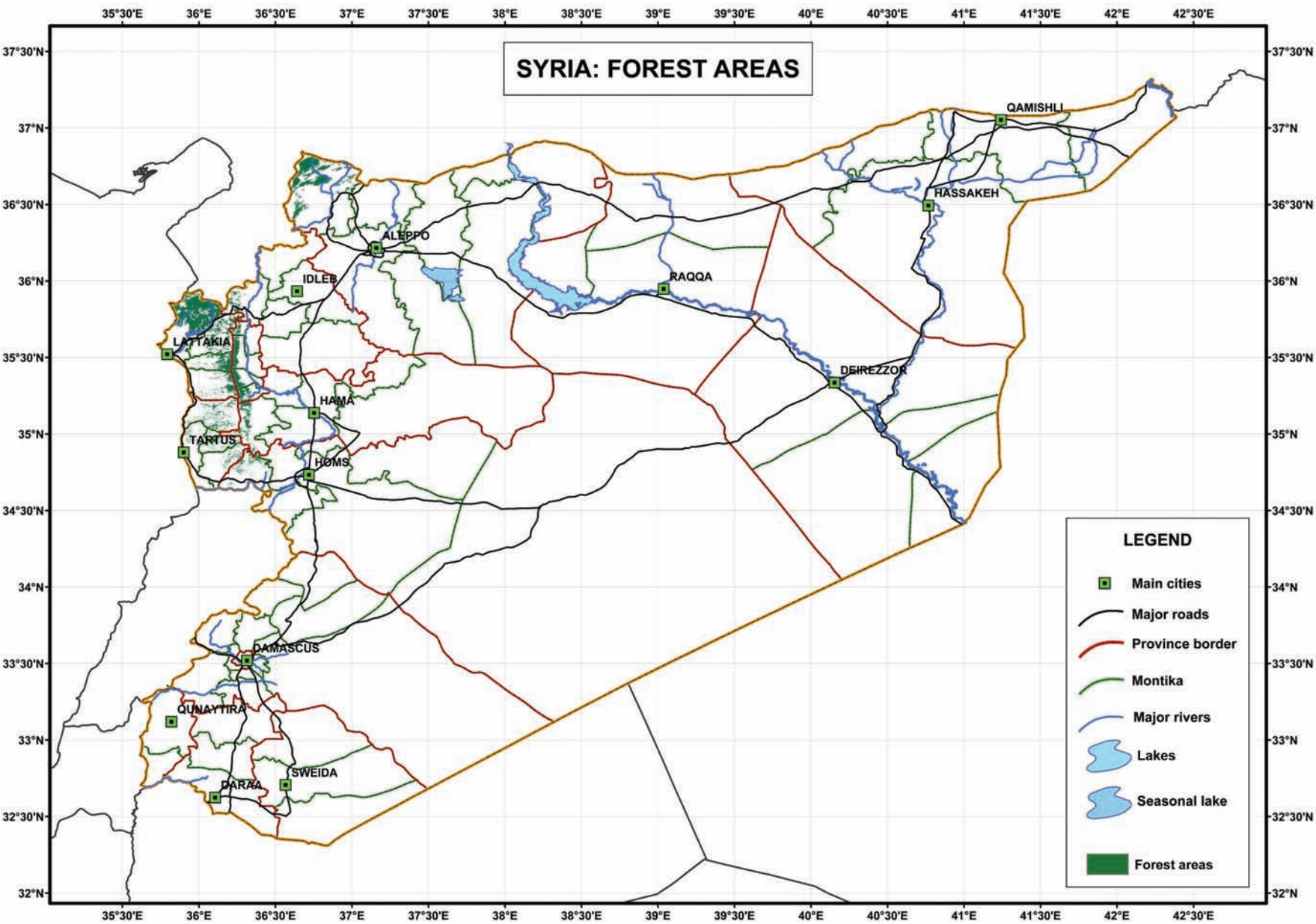
Annex 7. Maps

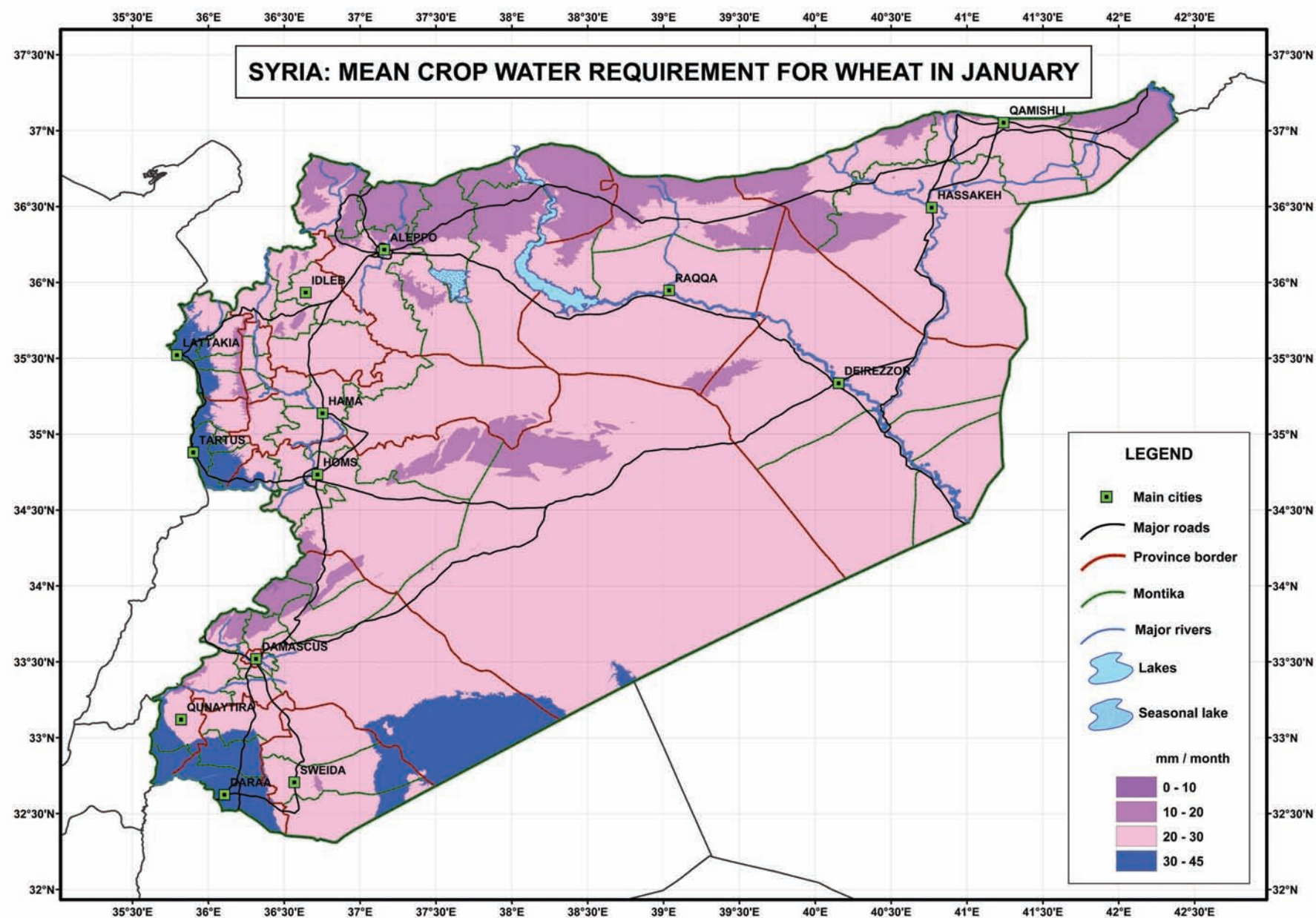
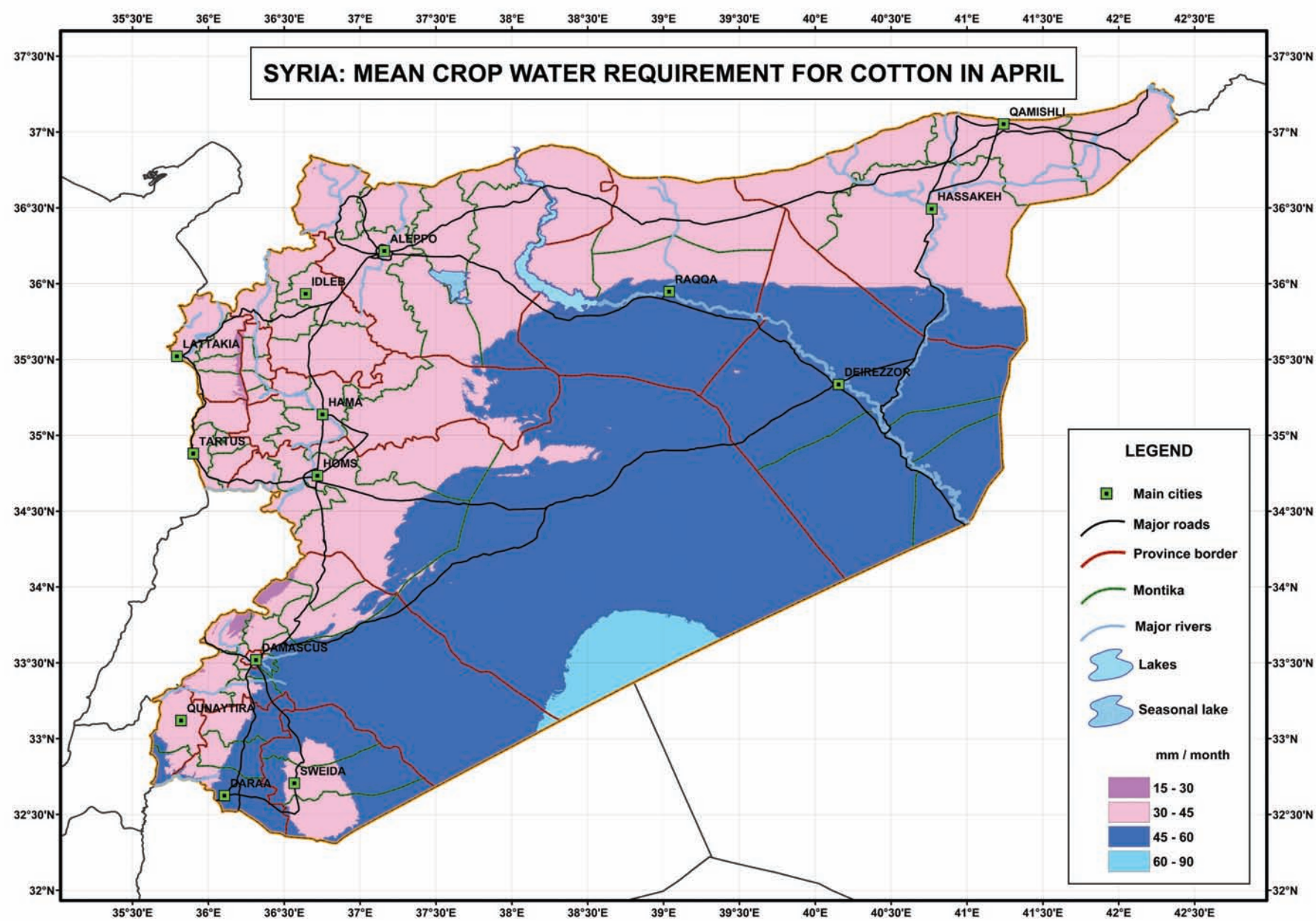
Title of Map

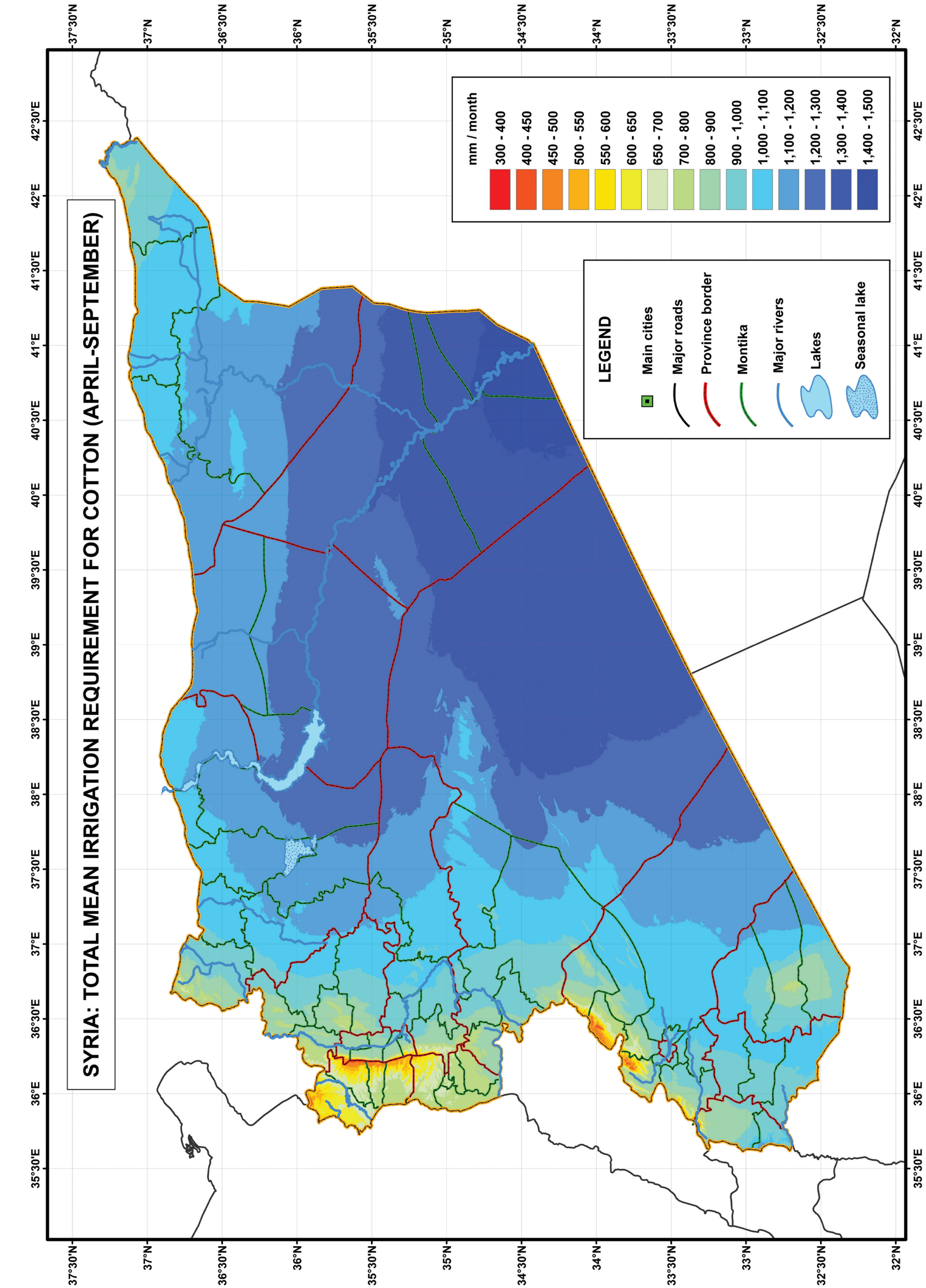
Slopes	28
Mean monthly precipitation in January	28
Mean monthly potential evapotranspiration in January	29
Summer irrigated areas	29
Forest areas	30
Arable land	30
Mean crop requirement for cotton in April	31
Mean crop water requirement for wheat in January	31
Total mean irrigation requirement for cotton (Apr-Sep)	32
Total mean irrigation requirement for wheat (Nov-May)	33
Potential water savings from shifting irrigated areas from fully irrigated cotton to wheat under supplemental irrigation	34
Distance from irrigated areas	34
Suitability rules: 1. Distance from irrigated areas	35
Suitability rules: 2. Slopes	35
Suitability rules: 3. Soils (arable land)	36
Suitability rules: 4. Forests	36
Combined suitability from distance, slopes, soils and forests	37
Modeled water allocations to rainfed areas	38

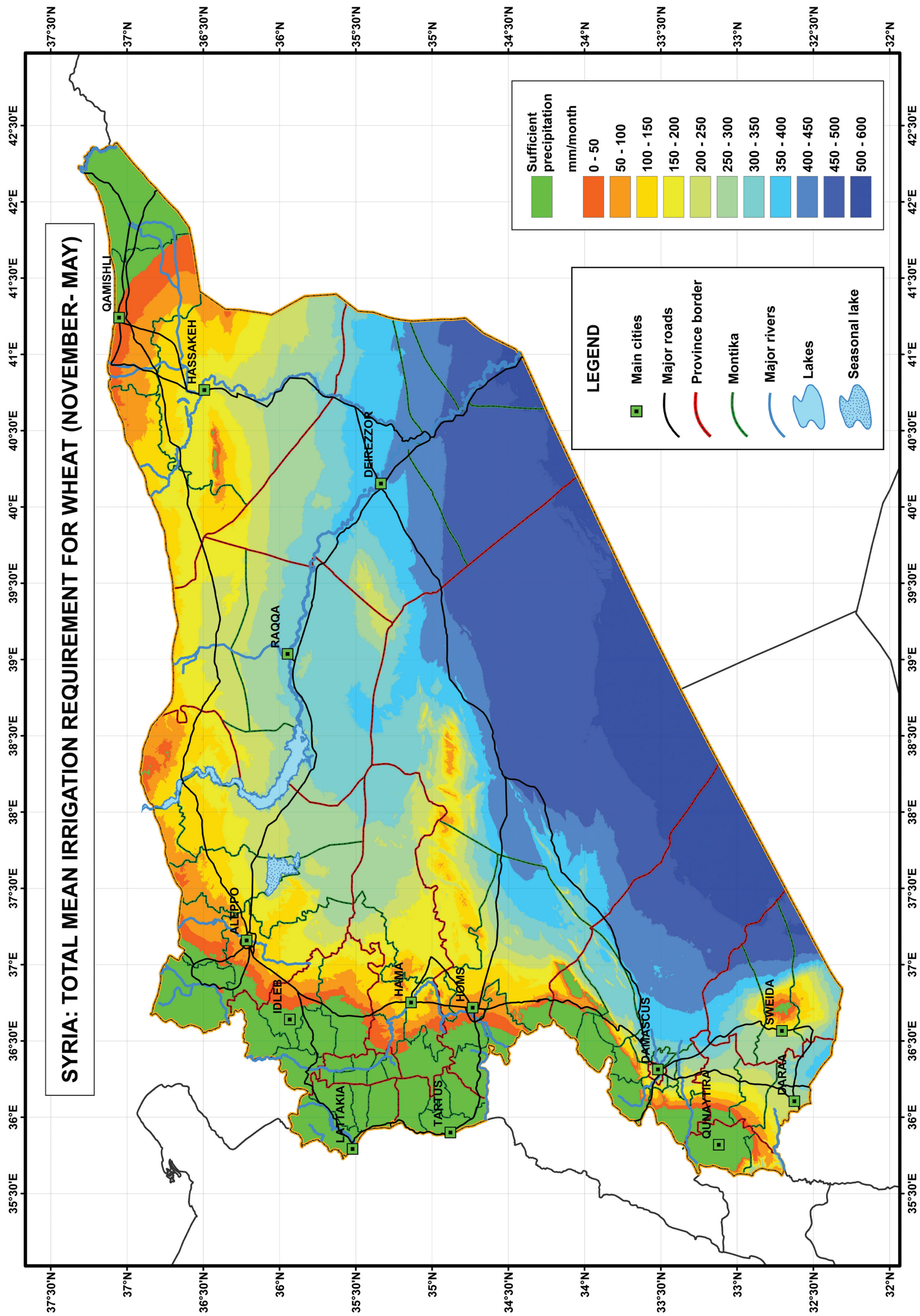


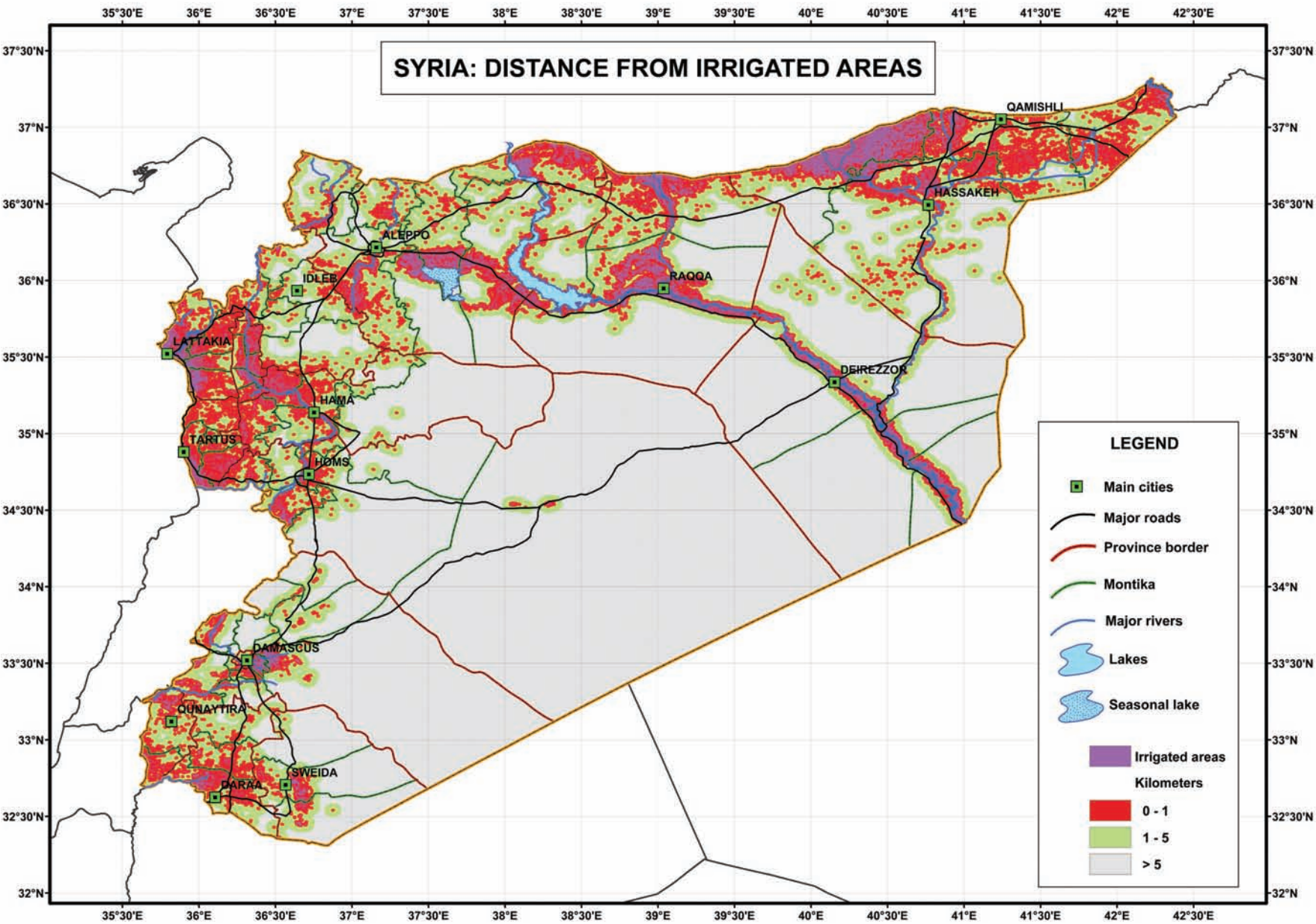
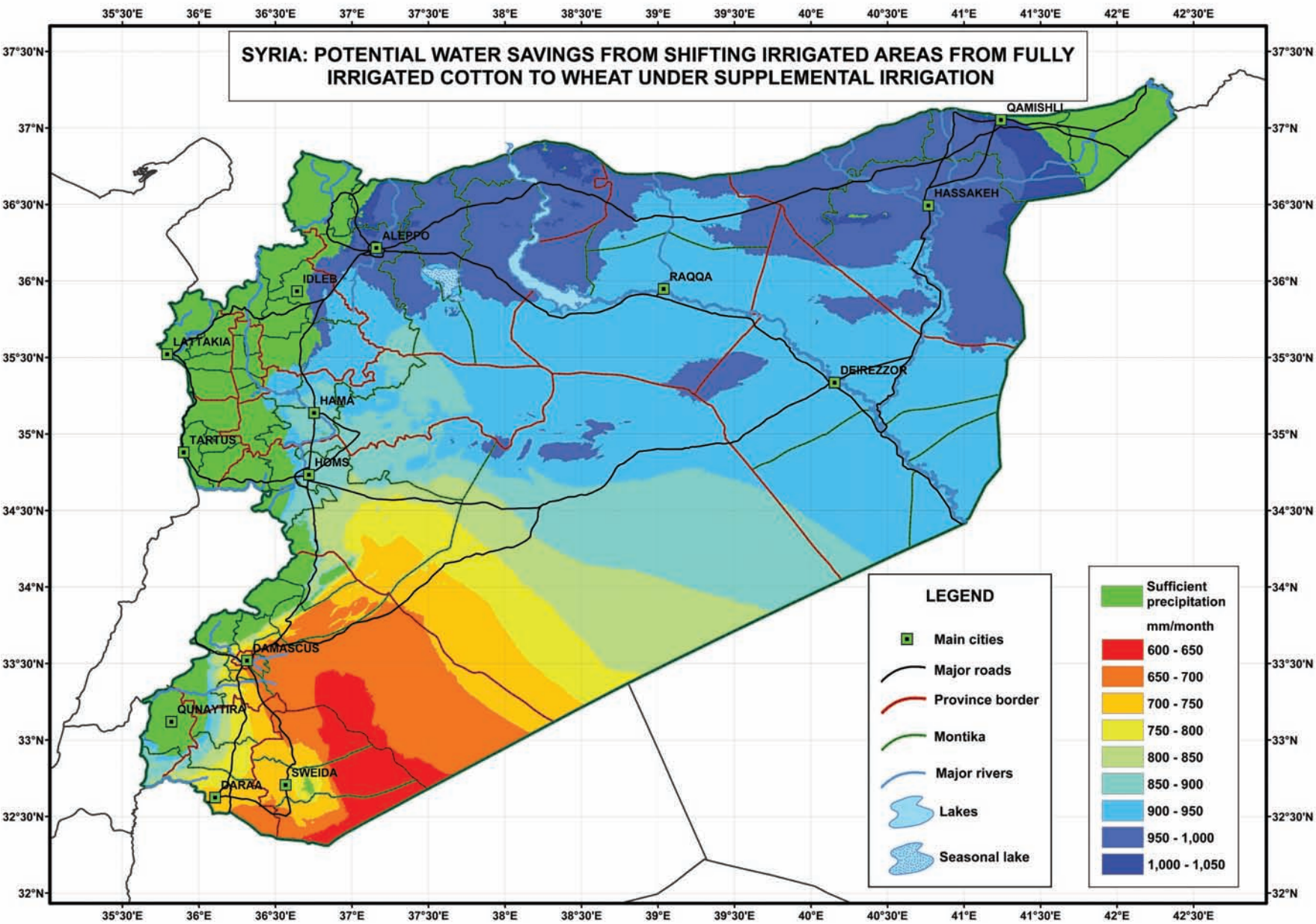


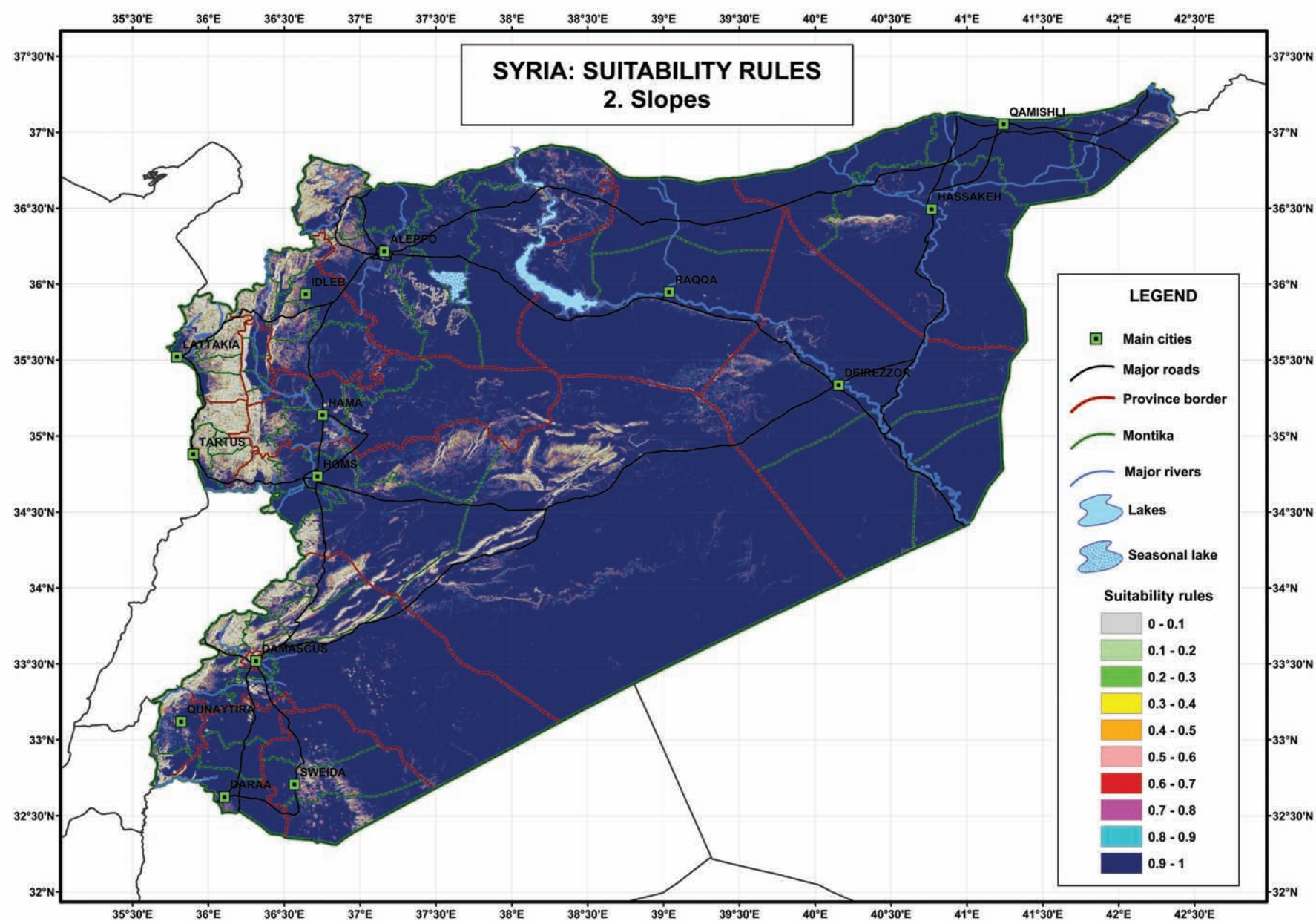
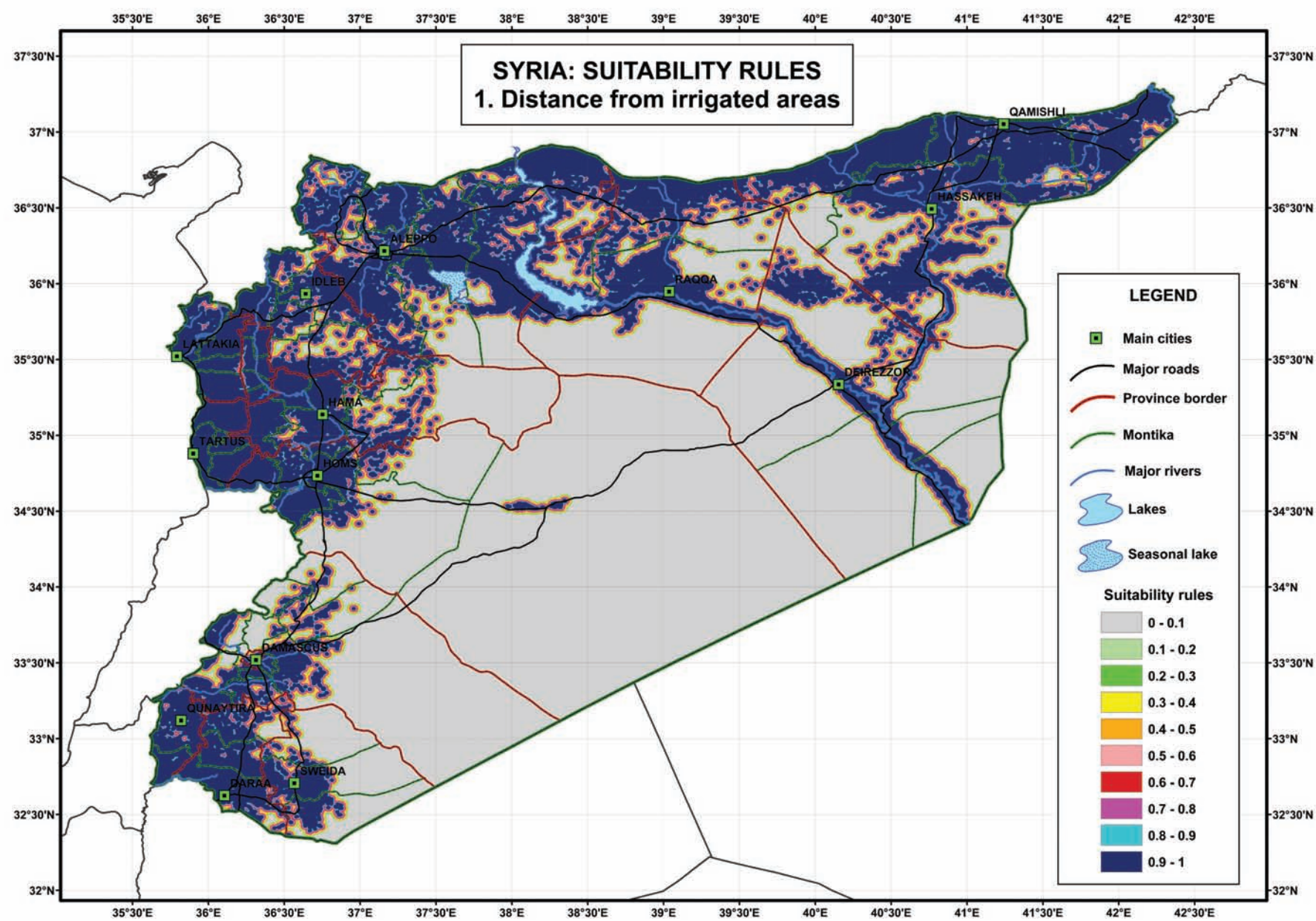


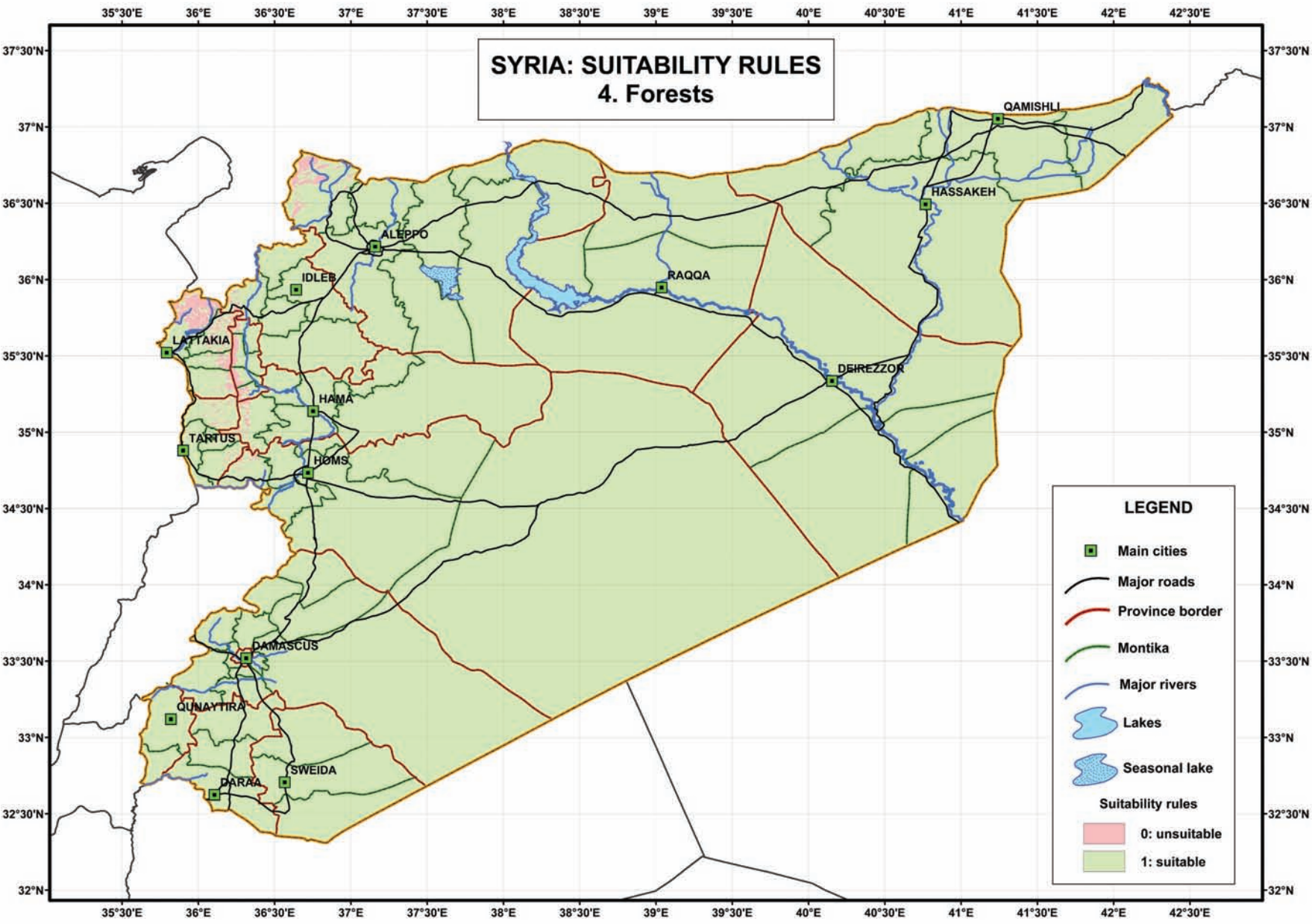
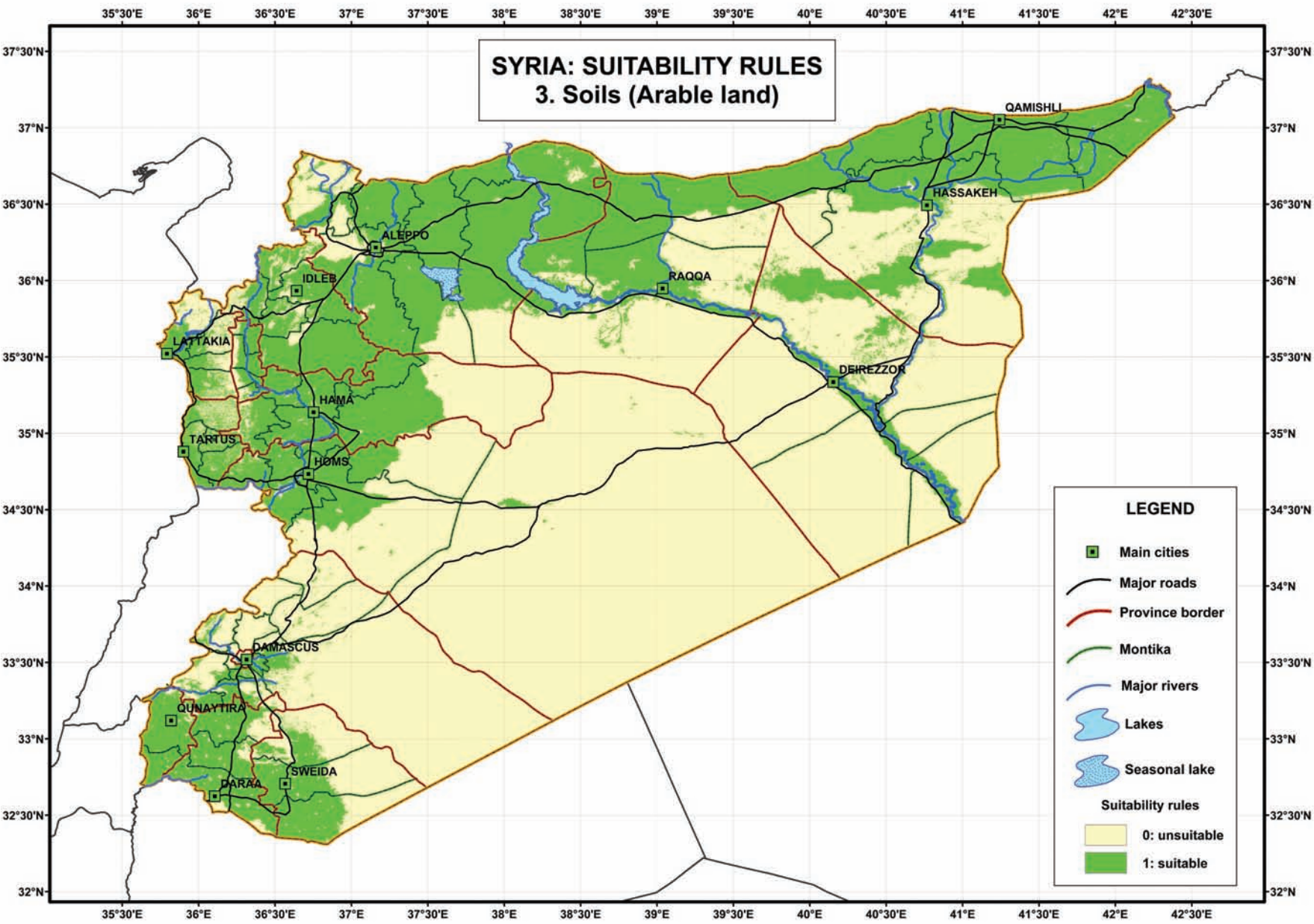


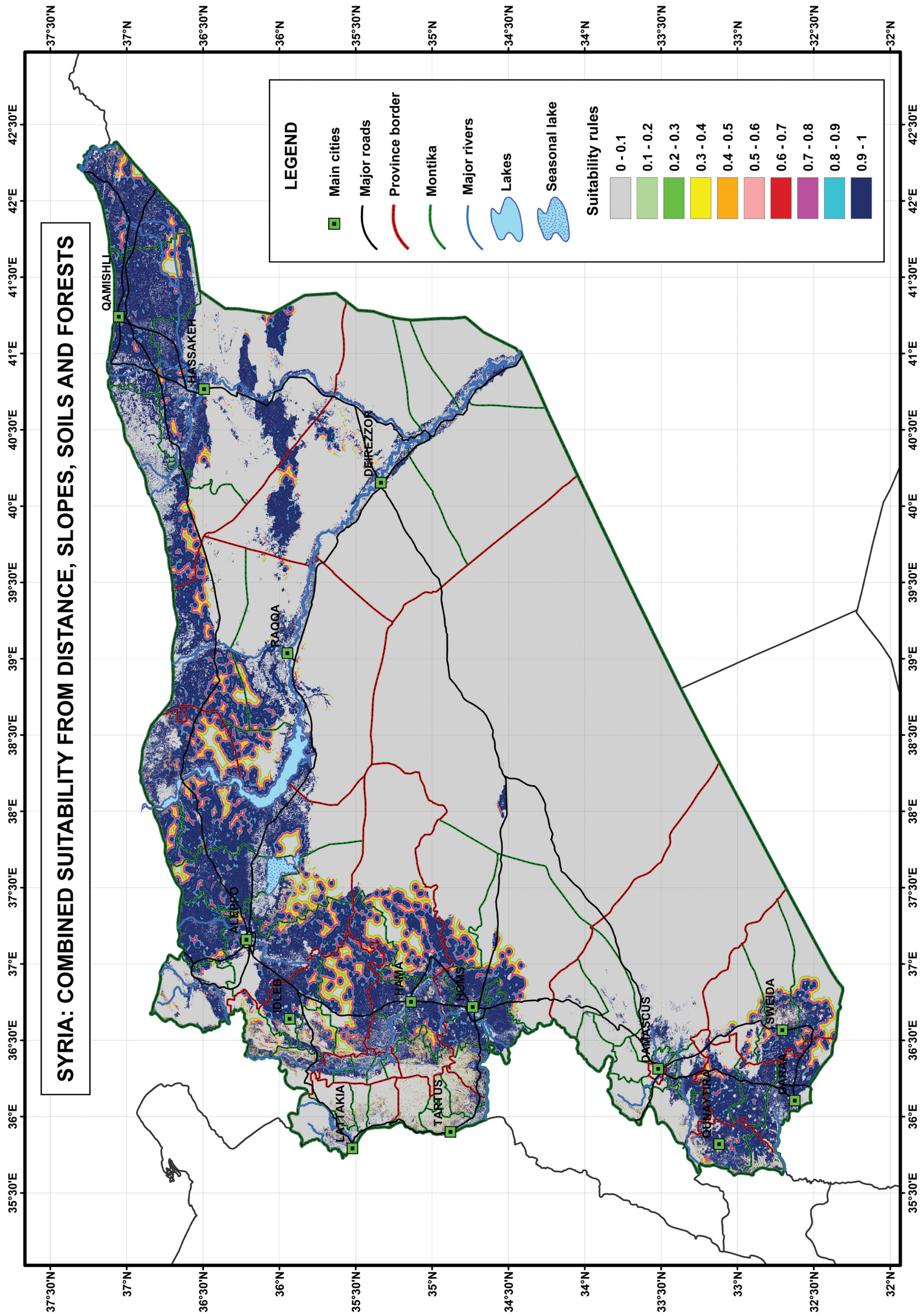


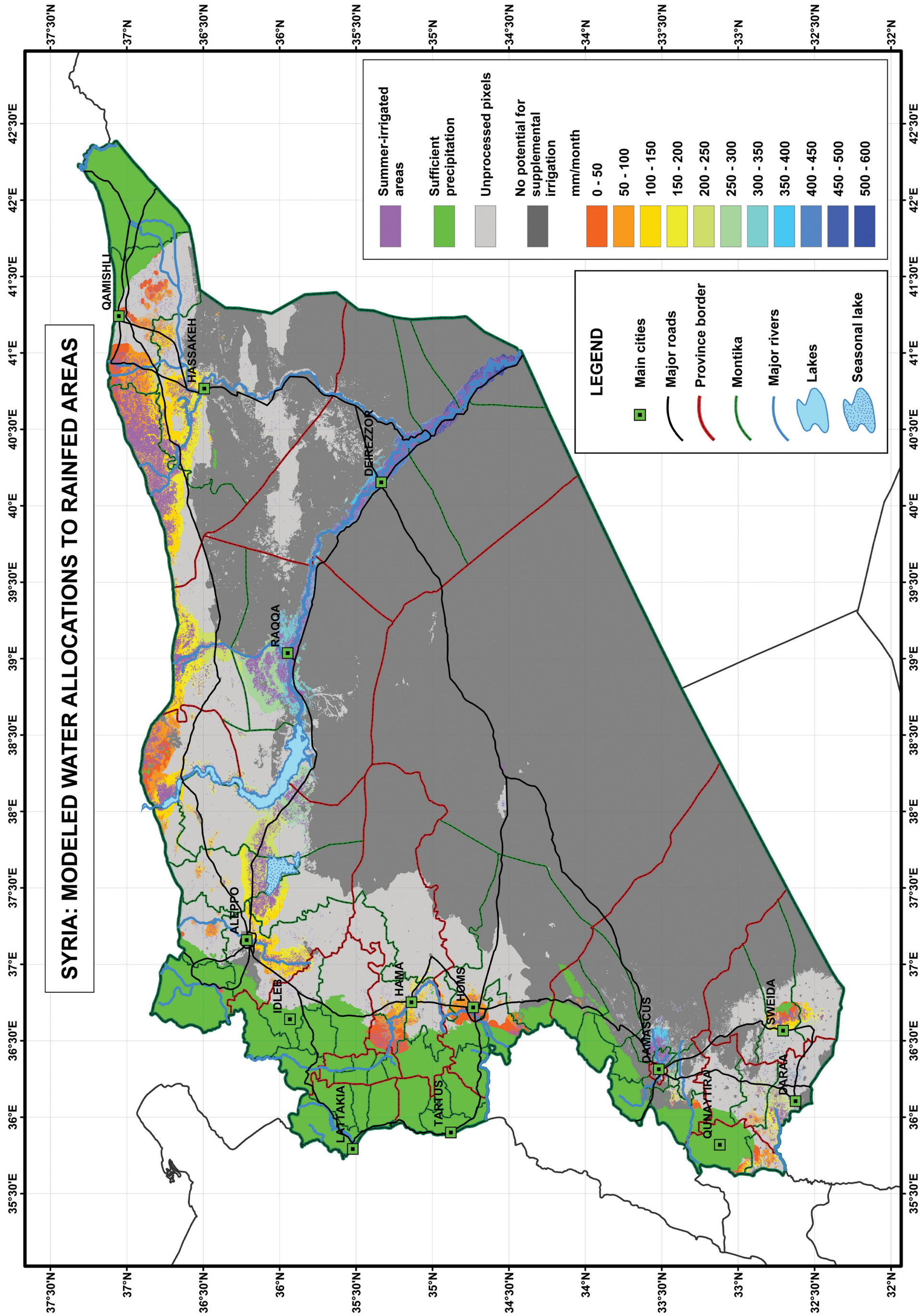






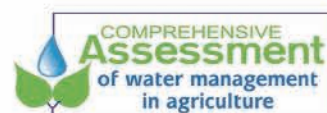








International Center for Agricultural Research in the Dry Areas
P.O. Box 5466, Aleppo, Syria



International Water Management Institute
P. O. Box 2075, Colombo, Sri Lanka