Remote sensing imagery invegetationmapping:areview

[1]SHREENANDAN SAHOO,
Gandhi Institute of Excellent Technocrats, Bhubaneswar, India

[2]PRITAM RANJAN PARIDA,
BRM League of Institution, Bhubaneswar, Odisha, India

Abstract

Aims
Mapping vegetation through remotely sensed images involves var-iousconsiderations,processesandtechniques.Increasingavail-ability of remotely sensed images due to the rapid advancementof remote sensing technology expands the horizon of our choicesof imagery sources. Various sources of imagery are known for theirdifferences in spectral, spatial, radioactive and temporal character-istics and thus are suitable for different purposes of vegetationmapping.Generally,itneedstodevelopavegetationclassificationat first for classifying and mapping vegetation cover from remotesensed images either at a community level or species level. Then,correlationsofthevegetationtypes(communitiesorspecies)within this classification system with discernible spectral charac-teristics of remote sensed imagery have to be identified. Thesespectral classes of the imagery are finally translated into the veg-etation types in the image interpretation process, which is alsocalledimageprocessing.Thispaperpresentsanoverviewofhow to use remote sensing imagery to classify and map vegetationcover.

Methods
Specifically,thispaperfocusesonthecomparisonsofpopularremotesensing sensors, commonly adopted image processing methods andprevailingclassificationaccuracyassessments.

Importantfindings
Thebasicconcepts,availableimagerysourcesandclassificationtech-niquesofremotesensingimageryrelatedtovegetationmappingwereintroduced, analyzed and compared. The advantages and limitationsof using remote sensing imagery for vegetation cover mapping wereprovidedtoiteratetheimportanceofthoroughunderstandingofthere-lated concepts and careful design of the technical procedures, whichcanbeutilizedtostudyvegetationcoverfromremotesensedimages.

Keywords: vegetation mapping·remote sensing sensors·imageprocessing·imageclassification

Introduction

Assessing and monitoring the state of the earth surface is a keyrequirement for global change research (Committee on GlobalChangeResearch,NationalResearchCouncil,1999;Junget*al*.2006;Lambin*etal*.2001).Classifyingandmappingvegetation isanimportanttechnicaltaskformanagingnaturalresourcesasvegetationprovidesabaseforalllivingbeingsandplaysanessentialroleinaffectingglobalclimatechange,suchasinflu-encing terrestrial CO_2 (Xiao *et al.* 2004). Vegetation mappingalsopresentsvaluableinformationforunderstandingthe nat-ural and man-made environments through quantifying vege-tationcoverfromlocaltoglobalscalesatagiventimepointorover a continuous period. It is critical to obtain current states ofvegetation cover in order to initiate vegetation protection andrestorationprograms(Egbert*etal*.2002;He*etal*.2005).Agood caseisdemonstratedbytheGAPAnalysisProgramsponsoredby US Geological Survey that aims at better conserving plantcommunities (http://gapanalysis.nbii.gov/). Strong preferencehas been given to acquire updated data on vegetation coverchanges regularly or annually so as to better assess the envi-ronmentandecosystem(Knight*etal*.2006).

Traditionalmethods(e.g.fieldsurveys,literaturereviews,map interpretation and collateral and ancillary data analysis),however,arenoteffectivetoacquirevegetationcoversbe-cause they are time consuming, date lagged and often too ex-pensive. Thetechnologyofremote sensing offers a practicaland economical means to study vegetation cover changes, es-pecially over large areas (Langley *et al.* 2001; Nordberg andEvertson 2003). Because of the potential capacity for system-atic observations at various scales, remote sensing technologyextendspossibledataarchivesfrompresenttimetoover severaldecadesback.Forthisadvantage,enormouseffortshave been made by researchers and application specialists todelineate vegetation cover from local scale to global scale byapplyingremotesensingimagery.Forexample,theInterna-tional Geosphere–Biosphere Program pioneered a global landcover mapping in the development of the Global Land CoverCharacterization (GLCC) Database that was based on 1-km Ad-vancedVeryHighResolutionRadiometer(AVHRR)in1992(http://edcsns17.cr.usgs.gov/glcc/).Similarly,incollaborationwith over 30 research teams from around the world, the JointResearch Institute in Italy implemented a similar project, theGlobalLandCover2000(GLC2000),in 1999 to map globalland coverand built upthe VEGA2000 dataset by extractingthedatafrom1-kmSPOT4-VEGETATIONimagery(http://www-gvm.jrc.it/glc2000/). Two years later, US NASA releasedthe database of global MODIS land cover based on monthlycomposites from Terra MODIS Levels 2 and 3 data betweenJanuaryandDecember2001(http://duckwater.bu.edu/lc/mod12q1.html).Themappingapproachesaswellastheirstrengths and weaknesses of the above global land cover prod-ucts were highlighted by Jung *et al.* (2006). At a smaller scale,thePan-EuropeanLandCoverMonitoringproject,aimedatestablishing a 1-km Pan-European Land Cover Database(Fig. 1), was initialized in 1996 to build a land cover databasecovering the entire European continent through the integra-tive use of multiple spectral–temporal NOAA–AVHRR satelliteimageryandancillarydata(Rounsevell*etal.*2006).

Besides these datasets at the global and continental scales,there have been numerous efforts taken over regional or na-tional extents to map vegetation. An example is the USGS–NPSVegetation Mapping, a collaborative program between the U.S.Geological Survey and the National Park Service, which beganin 1994 with the aim to produce detailed and computerizedmapsofthevegetationfor ≥ 250nationalparksacrossthe UnitedStatesbyprocessingAirborneVisibleandInfraredIm-agingSpectrometer(AVIRIS)imageryalongwithgroundsam-pling references. Remote sensing technology not only can beapplied to map vegetation covers over land areas but also inunderwaterareaswithfocusonmappingsubmergentaquaticvegetation(SAV),whichisregardedasapowerfulindicatorofenvironmental conditions in both marine and fresh water eco-systems(Lathrop*etal.*2006;Wolter*etal.*2005).

Wewillsynthesizeinthispaperacomprehensivereviewonhowtheremotesensingtechnologyisutilizedtoclassifyandmapvegetation cover. A survey of remote sensing sensors as well astheir suitability in vegetation mapping will be presented in nextsection. Image preprocessing and image classification methodscommonlyadoptedinextractingvegetationinformationfromremotesensedimages(includinghyperspectralimageryapplicationand data fusion) willbe illustrated in‘Vegetationex-traction from remote sensing imagery’. Classification resultevaluation (or accuracy assessment) will be discussed in ‘Resultevaluation’. Limitationsofusingimagerytomapvegetationcov-ersandrelateddiscussionswillbeconcludedinthefinalsection.

Remotesensingsensors

A remote sensing sensor is a key device that captures dataabout an object or scene remotely. Since objects (includingvegetation) have their unique spectral features (reflectanceor emission regions), they can be identified from remote sens-ingimageryaccordingtotheiruniquespectralcharacteristics.A good case in vegetation mapping by using remote sensingtechnologyisthespectralradiancesintheredandnear-infra-red regions, in addition to others. The radiances in theseregionscouldbeincorporatedintothespectralvegetationin-dices (VI) that are directly related to the intercepted fraction ofphotosyntheticallyactiveradiation(Asrar*etal.*1984;Galio

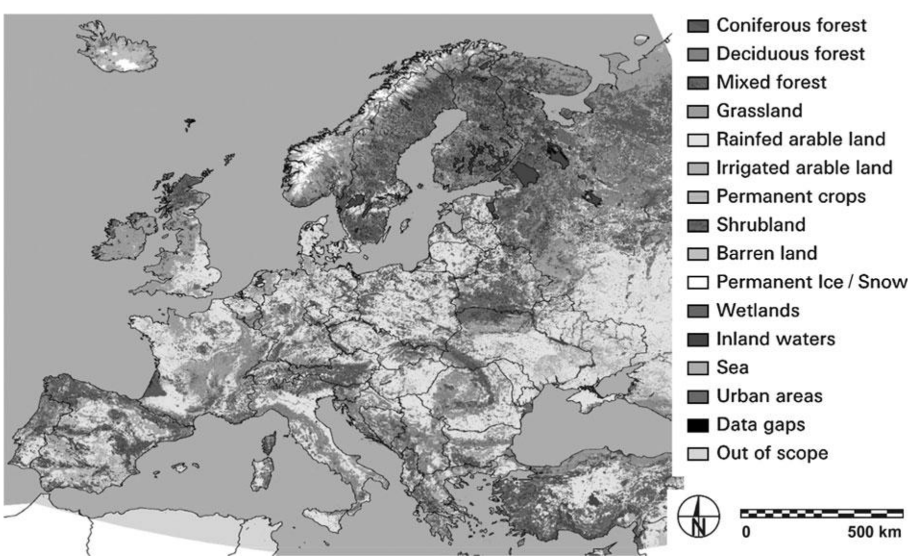

Figure1Pan-EuropeanLandCoverMonitoring1kmpan-EuropeanlandcoverderivedfromNOAA–AVHRRsatelliteimagery(fromhttp://www.geo-informatie.nl/projects/pelcom/public/index.htm).Acolourversionofthisfigureisavailableonlineassupplementarydata.

*etal.*1985).Thespectralsignaturesofphotosyntheticallyandnon-photosynthetically active vegetation showed obvious dif-ferenceandcouldbeutilizedtoestimateforagequantityandquality ofgrassprairie(Fig.2)(Beeri*etal.*2007).

Over the past half century, remote sensing imagery has beenacquired by a range of airborne and space-borne sensors frommultispectralsensorstohyperspectralsensorswithwave-lengths ranging from visible to microwave, with spatial reso-lutionsrangingfromsub-metertokilometersand withtemporalfrequenciesrangingfrom30minto weeks ormonths. The rough guidelines for definitions of spatial resolu-tionmaybedefinedasfollowing(Navulur2006):(i)loworcoarse resolution is defined as pixels with ground sampling dis-tance(GSD)of30morgreater,(ii)mediumresolutionisGSDin the range of 2.0–30 m, (iii) high resolution is GSD 0.5–2.0 m,and (iv) very high resolution is pixel sizes <0.5 m GSD. Sincedifferent sensors have different spatial, temporal, spectral andradiometric characteristics, the selection of appropriate sensorsis veryimportant for mapping vegetationcover. The selectionof images acquired by adequate sensors is largely determinedby four related factors: (i) the mapping objective, (ii) the cost ofimages,(iii)theclimateconditions(especiallyatmosphericconditions) and (iv) the technical issues for image interpreta-tion. First, the mapping objective concerns what is to be map-pedandwhatmappingaccuracyisexpected. In general,images with low resolutions may be adopted only when thehighlevelofvegetation classes are to be identified, whiletheimageswithrelativelyhigherresolutionsareusedforfine-detailedclassificationsofvegetation.Second,remotesensing imagery may be very expensive and the cost of imag-ery is definitely a consideration when choosing imagery. Fromthe mapping scale point of view, vegetation mapping at a smallscaleusuallyrequireshigh-resolutionimages,whilelow-resolutionimages are used for a large-scale mapping. Third,it raises the issue of the feasibility of using data from differentsources to obtain a cloud-free image series over an extendedperiodof time (Soudani*et al.* 2006).Lastly,some technical

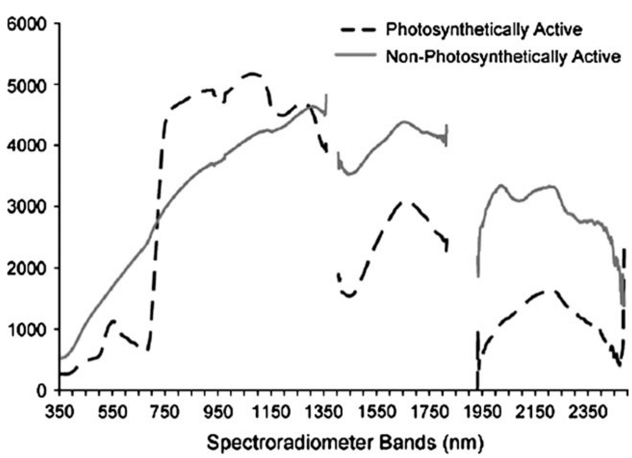

Figure 2 typical spectral signatures of photosynthetically active andnon-photosyntheticallyactivevegetation(Beeri*etal.*,2007).

specifics need to be taken into account regarding image qual-ity, preprocessing and interpretation when choosing suitablecandidatesofsensors. In the field of vegetation mapping,the most commonly applied sensors include Landsat (mainlyTMandETM+),SPOT,MODIS,NOAA–AVHRR,IKONOSand QuickBird. The characteristics of these sensors are summarizedinTable1anddescribedbelow.

LandsatTMandETM+

TheLandsatmighthavethelongesthistoryandwidestuseformonitoringtheearthfromspace.SincethefirstLandsatsatel-litewaslaunchedin1972,aseriesofmoresophisticatedmul-tispectral imaging sensors, named TM—Thematic Mapper,havebeenaddedrangingfromLandsats4(1982),5(1984), 6 (1993,launchfailed)to7 (1999)(Enhanced ThematicMap-perPlus,ETM+).TheLandsatTMandETM+ imagingsensorshavearchivedmillionsofimageswithanearlycontinuousre-cord of global land surface data since its inception. Landsat pro-videsmediumto coarsespatial resolutionimages. For example,LandsatETM+imageryhasaspatialresolutionof30mforthemultispectralbandsand60mforthethermalinfraredband.Landsat products have been applied in vegetation mappingmainlyatregionalscales.SinceLandsathasalonghistory ofdataset,itisveryhelpfultomaplong-termvegetationcoverand study the spatiotemporalvegetation changes. For exam-ple,nearly20-yearcontinuousLandsatTM/ETM+imagedata-sets(19images)coveringwesternOregonwereusedtodetectandcharacterizecontinuouschangesinearlyforestsuccession(Schroeder*etal*.2006).LandsatTMimages,stridingalongpe-riodoftimefrom1986to2002,wereusedtoconductquan-titativeanalysesofwetlandlandscapepatternsandtheirdynamicchangesintheestuaryoftheMinjiangRiver(Zheng*etal.*2006).BecauseofthedifferentcharacteristicsofspectralsensorsS(i.e.TMandETM+)intheLandsatimageseries,itisnecessarytocorrectthespectralreflectancebetweenimagesac-quiredbythosesensors.Thisisespeciallynecessaryinlong-term vegetation cover monitoring research where both LandsatTMandETM+imagesareused.Moran*etal.*(2001)proposed anempiricallineapproachforreflectancefactorretrievalfromLandsat-5TMandLandsat-7ETM+.Thecorrespondenceanalysismethodbasedonthespectraltransformationofindi-vidualdateimagesintoacomponentspacewasappliedtotwomulti-temporal Landsat images of Raleigh, North Carolina forlanduseandlandcoverchangedetection(Cakir*etal.*2006).Duetothelimitationofspatialresolution,Landsatproductsareusually usedtomapvegetationatcommunitylevel.Itisachallengingtask to use Landsat imagesformapping at specieslevel,especiallyinaheterogeneousenvironment.However,whenintegratingwithotherancillarydata,itbecomespossibletomapspecies.Anexampleofaspecieslevelofvegetationclassification wasimplementedintheAmanosMountainsregionofsoutherncentralTurkeyusingLandsatimages,com-binedwiththeenvironmentalvariablesandforestmanage-mentmaps,toproduceregionalscalevegetationmapswith anoverallhighaccuracy(DomaçandSüzen2006).

Table1mainfeaturesofimageproductsfromthedifferentsensors

Products(sensors)	Features	Vegetationmappingapplications[a]
LandsatTM	Mediumtocoarsespatialresolutionwithmultispectraldata(120mforthermalinfraredbandand30mformultispectralbands)fromLandsat4and5(1982topresent).Eachscenecovers anarea of1853185km.Temporalresolutionis16 days.	Regionalscalemapping,usuallycapableofmappingvegetationatcommunitylevel.
Landsat ETM+(Landsat7)	Mediumtocoarsespatialresolution with multispectral data(15mforpanchromaticband,60mforthermalinfraredand30mformultispectralbands)(1999topresent).Eachscenecoversanareaof185km3185km.Temporalresolutionis16days.	Regionalscalemapping,usuallycapableofmappingvegetationatcommunitylevelorsomedominantspeciescanbepossiblydiscriminated.
SPOT	Afullrangeofmediumspatialresolutionsfrom20mdownto 2.5m,andSPOTVGTwithcoarsespatialresolutionof1km.Eachscenecovers60360kmforHRV/HRVIR/HRGand100031000km(or200032000km)forVGT.SPOT1,2,3, 4 and 5 were launched in the year of 1986, 1990, 1993,1998and2002,respectively.SPOT1and3arenotprovidingdatanow.	Regionalscaleusuallycapableofmappingvegetationatcommunitylevelorspecieslevelorglobal/national/regionalscale(fromVGT)mappinglandcovertypes(i.e.urbanarea,classesofvegetation, waterarea,etc.).
MODIS	Lowspatialresolution(250–1000m)andmultispectraldatafromtheTerraSatellite(2000topresent)andAquaSatellite(2002topresent).Revisitintervalisaround1–2days.Suitableforvegetationmappingatalargescale.Theswathis2330km(crosstrack)by10km(alongtrackatnadir).	Mappingatglobal,continentalornationalscale.Suitableformapping landcovertypes(i.e.urbanarea,classes ofvegetation,waterarea,etc.).
AVHRR	1-kmGSDwithmultispectraldatafromtheNOAAsatelliteseries(1980topresent).Theapproximatescenesizeis240036400km	Global,continentalornationalscalemapping.Suitableformappinglandcovertypes(i.e.urbanarea,classesofvegetation,waterarea,etc.). Localtoregionalscalevegetationmappingatspeciesorcommunitylevelorcanbeusedtovalidateotherclassificationresult.
IKONOS	It collects high-resolution imagery at 1 m (panchromatic) and4 m (multispectral bands, including red, green, blue and nearinfrared)resolution.Therevisitrateis3–5days(off-nadir). Thesinglesceneis11311km.	Localtoregionalscalevegetationmappingatspeciesorcommunitylevel orused tovalidatevegetationcoverextractedfromotherimages.
QuickBird	High resolution (2.4–0.6 m) and panchromatic and multispectralimageryfromaconstellationofspacecraft.Singlesceneareais 16.5316.5km.Revisitfrequencyisaround1–3.5daysdependingonlatitude.	Regionaltonationalscalevegetationmappingatspeciesorcommunitylevel.
ASTER	Mediumspatialresolution(15–90m)imagewith14spectralbandsfromtheTerraSatellite(2000to present).Visibletonear-infraredbandshaveaspatialresolutionof15m,30mforshortwaveinfraredbandsand90mforthermalinfraredbands.	Atlocaltoregionalscaleusuallycapableofmappingvegetationatcommunitylevelorspecieslevel.Asimagesarecarriedoutasone-timeoperations,dataare notreadilyavailableasitisobtainedonan‘asneeds’basis.
AVIRIS	Airbornesensorcollectingimageswith224spectralbandsfromvisible,nearinfraredtoshortwaveinfrared.Dependingonthesatelliteplatformsandlatitudeofdatacollected,thespatialresolutionrangesfrommeterstodozensofmetersand theswathrangesfromseveralkilometerstodozensofkilometers.	Atregionalscalecapableofmappingvegetationatcommunitylevelorspecieslevel.
Hyperion	Itcollectshyperspectralimagewith220bandsrangingfromvisibletoshortwaveinfrared.Thespatialresolutionis30m.Dataavailablesince2003.	

[a]ManysensorsprovideimageryforproducingVI(e.g.NDVI)thatiscalculatedfromthebandsinthevisibleandnear-infraredregions.

In addition to the limitation caused by the medium spatialresolution of Landsat imagery, the relatively low temporal res-olution might also restrict its application in vegetation map-ping. Landsat satellites are popular and sun synchronous.
Ittakes ; 16daysforthesatellitestorevisitthelastlocation.Thisim posesaproblemforvegetationmappingusingLandsatim-ageryespeciallywhentheinterestofperiod(IOP)fallsina rainy season, during which heavy cloud greatly decreasestheimagequality.SinceIOPusuallyhaslimitedtime window,itisveryimportanttotakethemappingpurposeaswella sthelocal climate and topography conditions into account for theselectionofimagerysource. SPOT

TheimagesacquiredbySPOTEarthObservationSatellitesareus eful for studying, monitoring, forecasting and managing nat-uralresourcesandhumanactivities.FiveSPOTsatelliteshavebee n launched so far, from SPOT 1 to SPOT 5 in the year of1986,1990,1993,1998and2002,respectively.SPOTimagery comes in a full range of resolutions from 1 km global scale(SPOT vegetation imagery) down to 2.5 m local scale. TwoHRV (High Resolution Visible) imaging instruments on SPOT1, 2 and 3 and the corresponding instruments of HRVIR (HighResolution Visible and Infrared) on SPOT 4 and HRG (HighResolutionGeometry)onSPOT5scanineitherpanchroma tic

ormultispectralmodes.Inaddition,SPOT4and5alsohavea second imaging instrument referred to as SPOT vegetation(VGT) instrument that collects data at a spatial resolution of1kmandatemporalresolutionof1day.SPOTimages,partic-ularly SPOT VGT, are very useful for observing and analyzingthe evolution of land surfaces and understanding land changesover large areas. Because of the multiple sensor instrumentsand the revisit frequencies, SPOT satellites are capable ofobtaining an image of any place on earth every day and havingan advantage of mapping vegetation at flexible scales (re-gional,national,continentalorglobal).

Huang and Siegert (2006) studied the desertification pro-cessesbyusingtimeseriesofSPOTVGTimagesandproducedalan dcovermapwithaspecialemphasisonthedetectionofsparse vegetation in north China. A classification system fordifferentlandcovertypeswithaspecialemphasisonthesparseveg etation cover was developed to resolve problems related tothe seasonal changes and the highly variable natural condi-tions. As Huang and Siegert (2006) noted, SPOT VGT imageryisveryusefultodetectlarge-scaledynamicsofenvironmentalchanges due to the wide swath and sensitivity of the images tovegetation growth. From multi-temporal SPOT4 VGT sensordata,Wang*etal.*(2006)builtatwo-levellandcoverclassifica-tion system for identifying Poyang Lake Basin’s land coverclusters. At continental scale, Cabral *et al.* (2006) built a datasetof monthly composite images composed of daily SPOT VGTimagesanddevelopedamethodsuitableforproducingaland cover map of southern hemisphere Africa at a spatial resolu-tion of 1 km. In addition, SPOT imagery is also effective inmonitoring the distribution and growth of particular plants.For example, SPOT4 VGT was used to produce a vegetationmap and predict the distribution of nest-site habitats of easternNewZealandfalcons(*Falconovaeseelandiae*)inOtago(Math ieu*etal.*2006).Togetmoreaccuratemapping,SPOTimagescanbeinte grated with other remote sensing images. Millward *et al.*(2006) used medium-resolution satellite imagery to determinethechangesinthelandscapeofthecoastalzonenearSanya inHainan Province, China. After a search for suitable satellite im-agery, they found that an effective way to identify the changeswas to integrate data from different sensors (TM and ETM+images, in addition to SPOT 2 HRV images). Furthermore,SPOTimagerycanbeevenutilizedtomodelbiochem icalpro-cesses.Churkina*etal.*(2005)performedananalysisofannualnetec osystemexchangeandthelengthofthecarbonuptakeperiod using the enhanced vegetation index (EVI) of SPOT4VGT.

MODIS

MODIS (Moderate Resolution Imaging Spectroradiometer) isa key instrument on aboard of the Terra (EOS AM) and Aqua(EOS PM) satellites. Terra MODIS and Aqua MODIS togetherare able to view the entire earth’s surface every 1–2 days. ThegatheredimagesfromMODIS,including 36 spectral bandswith spatial resolutions ranging from 250 to 1 km, are mainlyappliedtomapvegetationdynamicsandprocessesatalarge scale. Due to the coarse spatial resolution, vegetation mappingat a local scale or regional scale is not recommended. However,image fusion by combining multiple imagery types can possi-bly lead to better mapping results. Knight *et al.* (2006) exam-inedthepotentialforclassifyingvegetationphenology-basedland cover over Albemarle-Pamlico estuarine system usingMODIS-NDVI 250 m 16-day composite data. They concludedthat a significant value could be added to MODIS imagerythroughcombiningandcomparingthemulti-temporalobser-vationswithsimilarclassificationsgeneratedfrommuchhigherspa tialresolutiondata.

AVHRR

Carried aboard the NOAA’s Polar Orbiting Environmental Sat-elliteseries, the AVHRRsensoris a broadband, 4-(AVHRR/1),5-(AVHRR/2)or 6- (AVHRR/3) channel scanning radiometerinthevisible,nearinfraredandthermalinfraredportionsof theelectromagneticspectrum.AVHRRimage datahave twospatialresolutions: ; 1.1kmforlocalareacoverage(LAC)and 5 km for global area coverage (GAC). They are both widelyusedtostudyandmonitorvegetationconditionsinecosys-tems, including forests, tundra, grasslands, agricultural lands,landcovermappingandproductionoflarge-scalemapsforthesesubjects.Oneoftheobvious advantages of AVHRR isthe low cost and the high probability of obtaining a cloud-freeview of the land surface. GLCC, as mentioned previously, wasproducedbasedonAVHRRimagedata.Aglobal8-kmfrac-tional vegetation cover dataset for 1982–2000 was also derivedfromtheNOAA–AVHRRLandPathfindernormalized differ-encevegetationindex(NDVI)data(ZengandRao2003).

BecauseAVHRRhasanimagearchive with long history(eversince1978whenthefirstAVHRRwas launched), it isvery useful to study long-term changes of vegetation. In thestudy of the natural ecosystems of the Northeast Region of

Bra-zil (NEB) where they experienced persistent drought episodesand environmental degradation recently, Barbosa *et al.* (2006)examined the spatial heterogeneity and temporal dynamics oftheNEBusinga20-year(1982–2001)timeseriesofNDVIobservationsderivedfrom AVHRRinstrument. Otherstudiesconducted using AVHRR include Julien *et al.* (2006), Gonzalez-Alonso *et al.* (2004) and Al-Bakri and Taylor (2003). Because ofthecoarsespatialresolution,AVHRRissuitablefora large-scalemapping.Atacontinentalscale,Mayaux*etal.*(1998)mapped thevegetation cover of CentralAfrica by using theAVHRR LACand GAC data. Han *etal.* (2005) used AVHRR datatocalculatethedailyNDVI.Inthesimilarway,Maselli andChiesi (2006) used AVHRR data to study Mediterranean forestproductivitybasedontheproductionofNDVI.

AVHRRimagerysufferscertainlimitationsincalibration,geometry, orbital drift, limited spectral coverage and variationsin spectral coverage especially in the early period of applica-tions. Its utility has been restricted because its use often intro-ducessubstantialerrorsatvariousstagesofprocessingandanalysis. Nevertheless,manyprojects (including GLCC) aim-ingat mapping vegetationcoversat continental toglobal scales havebeen carriedout using AVHRR for years simply becauseofitslowcostandeasyaccess.

IKONOS

IKONOS is a commercial sun-synchronous earth observationsatellite launched in 1999 and was the first to collect publiclyavailable high-resolution imagery at 1 and 4 m resolution. Ithas two imagery sensors, multispectral and panchromatic.Panchromatic sensor collects image at 1 m while the multi-spectral bands (including blue, green, red and near infrared)have a spatial resolution at 4 m. Both sensors have a swathwidth of 11 km and 3–5 days of revisit interval. The IKONOSobservations are at a spatial scale equivalent to field measure-ments typically carried out in ecological and land cover re-search.As such, the IKONOS observations may serve asa source of 'virtual' ground measurements for the lower spatialresolution,globalobservatories(Goward*etal.*2003).Ideally,IKONOS can be used to map vegetation cover at a local scale orvalidate vegetation cover classified from other remote sensingimages(Goward*etal.*2003).

QuickBird

Similar to IKONOS, QuickBird offers highly accurate and evenhigherresolutionimagerywithpanchromaticimageryat60–70cmresolutionandmultispectralimageryat2.4and 2.8 m resolutions. It is the only spacecraft able to offer sub-meter resolution imagery so far. QuickBird's global collectionsof images greatly facilitate applications ranging from land andasset management to ecology modeling (including vegetationmapping). QuickBird images are usually used to study specialtopics in relatively small areas (or at a local scale) since it isimpracticaltoapplyQuickBird imagery for applications inlarge area due to its high cost and rigid technical parameters.Wolter *et al.* (2005) used QuickBirdimagery to map SAV atthree sites across the Great Lakes and proved that QuickBirdsensor data were very useful for classifying SAV. Coops *et al.*(2006)evaluatedtheapplicabilityofQuickBirdmultispectralimageryindetecting,mappingandmonitoringtheforestrydamagescausedbybeetles.TheresultssuggestedthatQuickBirdimagery particularly had a valuable role to play in identifyingtreecrownswithredattackdamages.SimilartoIKONOS,images from QuickBirdcanbe used to map vegetation coveratalocalscaleorusedforvalidationpurpose.

Besides aforementioned sensors, there are many others. Forexample, Advanced Spaceborne Thermal Emission and Reflec-tion Radiometer (ASTER) is an imaging instrument flying onTerra. ASTER has been used to obtain detailed maps of landsurface,reflectanceandelevationinthestudyofhabitatpatterns (Tuttle*etal.*2006).Thetransmittedchargecoupledde-viceandinfraredmultispectralscanneronaboardofChinese–Brazilian Earth Resources Satellites, a cooperative programbetweenChinaandBrazil,acquireimageswithspatialresolu-tion from 20 to 256 m (Epiphanio 2005; Ponzoni *et al.* 2006).Whilemostsensorsaforementionedcollectmultispectralimageswithdozensofspectral bands,hyperspectralimageryacquired by some other sensors may have hundreds of spectralbands. Note that the principle for mapping vegetation coverfrom remote sensing images relies on the unique spectral fea-tures of different vegetation types. Thus, hyperspectral imag-ery contains more vegetation information and can be used formore accurate vegetation mapping. AVIRIS, for example, col-lectsimageswith224spectralbands.

Vegetationextractionfromremotesensingimagery

Vegetation extraction from remote sensing imagery is the pro-cess of extracting vegetation information by interpreting sat-elliteimagesbasedonthe interpretation elements such asthe image color, texture, tone, pattern and association infor-mation, etc. Diverse methods have been developed to do this.Those methods can be broadly grouped either as supervised orasunsuperviseddependingonwhetherornot true grounddata are inputted as references. General steps involved in veg-etation mapping include image preprocessing and image clas-sification. Image preprocessing deals with all preparatory stepsnecessarytoimprovethequalityof original images, whichthenresultsintheassignmentofeachpixelofthescenetoone of the vegetation groups defined in a vegetation classifi-cation system or a membership matrix of the vegetation groupsiffuzzyclassificationisadopted.

Imagepreprocessing

Preprocessing of satellite images prior to vegetation extractionis essential to remove noise and increase the interpretability ofimage data. This is particularly true when a time series of im-agery is used or when an area is encompassed by many imagessince it is essentially important to make these images compat-ible spatially and spectrally. The ideal result of image prepro-cessing is that all images after image preprocessing shouldappear as if they were acquired from the same sensor (Hall*et al.* 1991). Botanist and ecologist should keep in mind thatwhile image preprocessing is the prerequisite for vegetationextraction from remote sensing images, the preprocessing pro-cedures listed below may not be always needed because someof these preprocessing procedures may have been done by im-agedistributionagencies.Thus,itisrecommendedtoconsultwith the image distributor and get to know at what level theimagery is (usually including level 0, 1A, 1B, 2A, 2B, 3A, 3Bwith image quality gradually increased) before imagery pur-chase. For example, for most sensors, level 3A means thatradiometric correction, geometric correction and orthorectifi-cation have been processed for the images. Image preprocess-ingcommonlycomprisesaseriesofoperations,includingbutnot limited to bad lines replacement, radiometric correction,geometric correction, image enhancement and masking (e.g.forclouds,water,irrelevantfeatures)althoughvariationsmayexistforimagesacquiredbydifferentsensors.

Bad line replacement is to determine the overall quality oftheimages(e.g.missingdatalines)throughvisually previewing the images band-by-band. The visual review isusuallydoneatfullextentswhileattentionisfocusedoniden-tifyinglinesorblocksofmissingdataineachbandforfurtherrepairing. Image line replacement is a procedure that fills inmissing lines with the line above, below or with an averageofthetwo.

Radiometriccorrectionofremotesensingdatanormallyinvolves the process of correcting radiometric errors or distor-tions of digital images to improve the fidelity of the brightnessvalues. Factors such as seasonal phenology, ground conditionsandatmosphericconditionscancontributetovariabilityin multi-temporalspectralresponsesthatmayhavelittletodowiththe remote sensed objects themselves (SongandWoodcock2003).Itismandatorytodifferentiate real changes fromnoises through radiometric correction in cases where the spec-tral signals are not sufficiently strong to minimize the effects ofthese complicating factors. Several methods are available tomake radioactive corrections. Some of them are based on com-plex mathematical models that describe the main interactionsinvolved. However, the values of certain parameters (i.e. theatmosphericcomposition)mustbeknownbeforeapplyingthem. Otherradiometriccorrection methods are based onthe observations of reference targets (e.g. water or desert land)whose radiometry is known. Whatever radiometric correctionmethodsare,theycanbeclassifiedintotwotypes:absolute andrelativecorrection(Cohen*etal.*2003;Coppin*etal.*2004;Du*et al.* 2002; Elvidge *et al.* 1995). The absolute radiometric cor-rection is aimed toward extracting the absolute reflectance ofscene objects at the surface of the earth, requiring the input ofsimultaneousatmosphericpropertiesandsensorcalibration,whicharedifficulttoacquire in many cases (Chen *et al.*2005; Du *et al.* 2002; Song *et al.* 2001). On the other hand,the relative radiometric correction is aimed toward reducingatmospheric and other unexpected variations among multipleimages by adjusting the radiometric properties of target imagesto match a base image (Hall *et al.* 1991), which proves to beeasiertoapply.Schroeder*et al.* (2006) and Chen *et al.*(2005) extensively compared the effectiveness of the absoluteradiometric correction methods (6S model, MDDV model andDOS model) and the relative radiometric correction methods(MADmodelandPIFmodel)andillustratedtheprosandconsofeachmodel.

Geometriccorrectionisaimedtoavoidgeometricdistortions from a distorted image and is achieved by establishing the re-lationship between the image coordinate system and the geo-graphiccoordinatesystemusingthecalibrationdataofthesensor,the measureddataofpositionandaltitudeandtheground control points. Therefore, geometric correction usuallyincludes the selection of a map projection system and the co-registrationofsatelliteimagedatawithotherdatathatareusedas the calibration reference. The outcome of geometric correc-tion should obtain an error within plus or minus one pixel of itstrueposition,whichallowsforaccuratespatial assessmentsand measurements of the data generated from the satellite im-agery.Thefirst-ordertransformationandthenearestneighborresampling of the uncorrected imagery are among those pop-ularlyadoptedmethodsingeometriccorrection.The first-order transformation, also known as the linear transformation,applies the standard linear equation (y = mx + b) to the X and Ycoordinates of the ground control points. The nearest neighborresampling method uses the value of the closest pixel to assignto the output pixel value and thus transfers original data valueswithout averaging them. Therefore, the extremes and subtle-tiesofthedatavaluesarenotlost(ERDAS1999).

Sometimes the images will be more distinguishable for in-terpretation if image enhancement is performed, which isaimed to emphasize and sharpen particular image features(i.e. particular species of vegetation) for visualization purpose.Thetraditionalimageenhancementincludegrayscaleconversion, histogram conversion, color composition, colorconversionbetweenred-green-blue (RGB) andhue–saturation–intensitytransform(HSI),etc.,whichareusuallyappliedtotheimageoutputforimageinterpretation.ShyuandLeou(1998)explained the limitations of traditional image enhancementmethodsandproposedageneticalgorithmapproachthatwasprovedmoreeffectivethanthetraditionalones.

Inmappingvegetationcoverusingremotesensingimages,especially mapping over large regions, cloud imposes a bignoise for identifying vegetation and thus has to be removedor masked. Jang *et al.* (2006) proposed a neural network to de-tect cloud in SPOT VEGETATION images. Walton and Morgan(1998) used cloud-free space shuttle photograph to detect andremove(mask)unwantedcloudcoversinLandsatTMscenes.

Imageclassification

Image classification, in a broad sense, is defined as the processof extracting differentiated classes or themes (e.g. land use cat-egories, vegetation species) from raw remotely sensed satellitedata. Obviously this definition includes the preprocessing ofimages.Weheresimplyrefertotheprocessfollowingtheim-agepreprocessingasimageclassification.Techniquesforextracting vegetation from preprocessed images are groupedintotwotypes:traditionalandimprovedmethods.

Traditionalmethods

Thetraditionalmethodsemploytheclassicalimageclassifica-tion algorithms, e.g. K-mean and ISODATA for unsupervisedclassification or the maximum likelihood classification (MLC)for supervised classification. Unsupervised approach is oftenused in thematic mapping (including vegetation cover map-ping)fromimagery.Itiseasytoapplyandwidelyavailablein image processing and statistical software packages (Langley*etal.*2001).TwomostfrequentlyusedmethodsaretheK - meanandtheISODATAclusteringalgorithms.Bothofthesealgorithms involve iterative procedures. In general, both ofthemassignanarbitraryinitialclustervectorfirst.Thesecondstep classifies each pixel to the closest cluster. In the third step,the new cluster mean vectors are calculated based on all thepixelsinonecluster.Thesecondandthirdstepsarerepeateduntilthegapbetweentheiterationissmallenough(orsmaller thanapresetthreshold).Unsupervisedclassificationmethodsare purely relying on spectrally pixel-based statistics and incor-porate no priori knowledge of the characteristics of the themesbeingstudied.Thebenefitofapplyingunsupervisedclassifica-tionmethodsistoautomaticallyconvertrawimagedataintouseful information so long as higher classification accuracy isachieved(TsoandOlsen2005).Alternatively,ratherthanpurely spectral,TsoandOlsen(2005)incorporatedbothspec-tral and contextual information to build a fundamental frame-workforunsupervisedclassification,HiddenMarkovModels,which showed improvements in both classification accuracyandvisualqualities.Algorithmsofunsupervisedclassificationwereinvestigatedandcomparedwithregardtotheirabilities to reproduce ground data in a complex area by Duda andCanty (2002). Despite its easy application, one disadvantageof the unsupervised classification is that the classificationprocess has to be repeated again if new data (samples) areadded.

By contrast, a supervised classification method is learningan established classification from a training dataset, whichcontains the predictor variables measured in each samplingunit and assigns prior classes to the sampling units (Lenkaand Milan 2005). The supervised classification is to assignnew sampling units to the priori classes. Thus, the additionofnewdatahas no impact on the established standardsofclassificationoncetheclassifierhasbeensetup.MLCclassifierisusuallyregardedasaclassicandmostwidelyusedsupervised classification for satellite images resting on thestatisticaldistributionpattern(Sohnand Rebello 2002;Xu*etal.*2005).However,MLCshowslesssatisfactorysuccesses since the MLC assumption that the data followGaussian distribution may not always be held in complexareas.

Improvedclassifiers

Itisverycommonthatthesamevegetationtypeongroundmay have different spectral features in remote sensed images.Also, different vegetation types may possess similar spectra,which makes very hard to obtain accurate classification resultseither using the traditional unsupervised classification or su-pervisedclassification.Searchingforimprovedclassificationmethodsisalwaysahotresearchtopic.However,strictlyspeaking, all classification methods are derived from the tradi-tionalmethodsasaforementioned,whichprovidethebasicprinciples andtechniquesforimageclassification.Thus,im-provedmethodsusuallyfocusonandexpandonspecifictechniquesor spectralfeatures,whichcanleadtobetterclassification results and thus deserve special attention. Greatprogress has been made in developing more powerful classi-fiers to extract vegetation covers from remote sensing images.For example, Stuart *et al.* (2006) developed continuous classi-ficationsusingLandsatdatatodistinguishvariationswithinNeotropical savannas and to characterize the boundaries be-tween savanna areas, the associated gallery forests, seasonallydryforestsandwetlandcommunities.Theyprovedthat continuousclassificationswerebetterthanMLCclassificationespeciallyincomplexlandcoverareas.

Extensive field knowledge and auxiliary data may help im-prove classification accuracy. Studies have shown that classi-fication accuracy can be greatly improved after applying expertknowledge (empirical rules) and ancillary data to extract the-matic features (e.g. vegetation groups) (Gad and Kusky 2006;Shrestha and Zinck 2001). In a regional scale vegetation clas-sificationconductedintheAmanosMountainsregionofsoutherncentral Turkey using Landsat images, Domaxc andSüzen(2006)incorporatedvegetation-relatedenvironmentalvariablesandconsiderablyimprovedclassificationaccuracywhencomparedwiththetraditional MLC method. Undermanycircumstances, however, gathering specific knowledgeis an enormous task and obtaining ancillary data is very costly.Therefore, the knowledge-based classifications are not univer-sallyapplicable.

Sohn and Rebello (2002) developed supervised and unsu-pervised spectral angle classifiers (SAC), which take accountofthefactthatthespectraofthesametypeofsurfaceobjects are approximately linearly scaled variations of one anotherdue to the atmospheric and topographic effects. Those SAChelped identify the distances between pairs of signatures forclassification and were successfully applied in biotic commu-nity and land cover classification (Sohn and Qi 2005). Theadoption of VI including the most widely used NDVI and itsrefinedform,EVI,isanothermethodtomapvegetationusingopticalremotesensingdevices(deFries*etal.*1995).Theprin-ciple of applying NDVI in vegetation mapping is that vegeta-tionishighlyreflectiveinthenearinfraredandhighlyabsorptive in the visible red. The contrast between these chan-nels can be used as an indicator of the status of the vegetation.Inotherword,NDVIisabiophysicalparameterthatcorrelateswithphotosyntheticactivityofvegetation.Inadditiontopro-viding an indication of the ‘greenness’ of the vegetation (WangandTenhunen2004),NDVIisalsoabletooffervaluableinfor-mationofthedynamicchangesofspecificvegetationspeciesgiven that multiple-time images are analyzed. Therefore, NDVIis a good indicator to reflect periodically dynamic changes ofvegetationgroups(Geerken*etal.*2005).Particularvegetationgroups can be identified through their unique phenology, ordynamic signals of NDVI (Lenney *et al.* 1996), which is alsoknown as ‘Multitemporal Image Classification’. Another ap-proach to identify specific vegetation groups is to study timeseries VI. For example, Bagan *et al.* (2005) applied the com-binedEVImulti-datasetgeneratedfrom16-dayintervalMODIS data during the growing season of plants as inputparameters to match the features of vegetation groups andto classify the images. The classification results were comparedwiththoseofthetraditionalMLCmethodandtheaccurac yoftheformerexceededthatofthelatter.

Artificialneuralnetwork(ANN)andfuzzylogicapproaches are also seen in literature for vegetation classifications. ANNis appropriate for the analysis of nearly any kind of data irre-spectiveoftheirstatisticalproperties.ANNisveryusefulin extracting vegetation-type information in complex vegetationmappingproblems(FilippiandJensen2006),thoughitisat theexpense oftheinterpretabilityoftheresultssinceANNdeploys a black-box approach that hides the underlying pre-dictionprocess(ČernáandChytrý2005).Berberoglu*etal.* (2000) combined ANN and texture analysis on a per-field basisto classify land cover and found the accuracy could be 15%greaterthantheaccuracyachievedusingastandardper-pixelML classification. One disadvantage of ANN, however, is thatANNcanbecomputationallydemandingwhenlargedatasetsare dealt to train the network and sometimes no result may beachievedatallevenafteralong-timecomputationduetothelocalminimum(e.g.foraback-propagationANN).

Afuzzyclassificationapproachisusuallyusefulinmixed-classareas and wasinvestigatedfor the classificationof suburbanlandcover from remote sensing imagery (Zhang and Foody 1998),the study of medium-to-long term (10–50 years) vegetationchanges(OkekeandKarnieli2006)andthebiotic-basedgrass-land classification (Sha *et al.* 2008). Fuzzy classification is a kindof probability-based classification rather than crisp classifica-tion. Unlike implementing per-pixel-based classifier to producecrisp or hard classification, Xu *et al.* (2005) employed a decisiontree(DT) derivedfromtheregressionapproachtodetermineclassproportionswithinapixelsoastoproduceasoftclassifi-cation.Theoretically,probability-basedorsoftclassificationismorereasonableforcompositeunitssincethoseunitscannotbesimplyclassifiedtoonetypebuttoaprobabilityforthattype.While soft classification techniques are inherently appealing formappingvegetationtransition,thereisanunresolvedissueofhowbesttopresenttheoutput.Ratherthanimposingsubjec-tive boundaries on the end-member communities, transitionzones of intermediate vegetation classes between the end-member communities were adopted to better represent thesoftenedclassificationresult(Hill*etal.*2007).

DTisanotherapproachofvegetationclassificationbymatching the spectral features or combinations of spectralfeatures from images with those of possible end members ofvegetationtypes(communityorspecieslevel).DTiscomputationally fast, makes no statistical assumptions andcan handle data that are represented on different measure-ment scales. A global land cover map deduced from AVHRRimagerywasproducedbyHansen*etal.*(2006)usingaDTthathas a set of 41 metrics generated from five spectral channelsandNDVIforinput.Theagreementsforallclassesvariedfroman average of 65% when viewing all pixels to an average of82% when viewing only those 1 km pixels consisting of >90% one class within the high-resolution datasets. Otherstudiesintegratedsoftclassificationwith DTapproach(Xu *et al.* 2005). Pal and Mather (2003) studied the utility of DTclassifiersforlandcoverclassificationusing multispectraland hyperspectral data and compared the performance oftheDTclassifierwiththatoftheANNandMLclassifiers,withchanges in training data size, choice of attribute selectionmeasures, pruning methods and boosting. They found thattheuseofDTclassifierswithhigh-dimensional(hyperspectral data) is limited while good result was achieved with multispec-tral data. Under some circumstances, DT can be very usefulwhen vegetation types are strictly associated with other natu-ral conditions (e.g. soil type or topography) (He *et al.* 2005). Forexample, some vegetation species may only grow in areas withelevation higher than a certain level. This can be integratedwithin DT to assist the classification process from imagery ifsuchancillarydataareavailable.

InthestudyofmonitoringnaturalvegetationinMediterra-nean, Sluiter (2005) investigated a wide range of vegetationclassification methods for remote sensing imagery. Firstly,twomethodsofrandomforestsandsupportvectormachineswere explored, which showed better performances over thetraditionalclassificationtechniques.Secondly,ratherthanus-ing the per-pixel spectral information to extract vegetation fea-tures, Sluiter applied the spatial domain, viz. both per-pixelspectral information and the spectral information of neighbor-ing pixels to analyze and classify remote sensing imagery. Itwas found that when a contextual technique named SPARK(SPAtial Reclassification Kernel) was implemented, vegetationclasses, which were not distinguished at all by conventionalper-pixel-based methods, could be successfully detected. Thesimilar result was also noted by Im and Jensen (2005) whousedathree-channelneighborhoodcorrelationimagemodelto detect vegetation changes through the relation of pixels andtheir contextual neighbors. Based on SPARK, Sluiter (2005)continuedintegratingspectralinformation,ancillaryinforma-tion and contextual information and developed a spatiotempo-ral image classification model called ancillary data classificationmodel(ADCM).TheADCMmethodincreasedtheoverallaccu-racy as well as individual class accuracies in identifying hetero-geneousvegetationclasses.

As stated above, there are many classification methods oralgorithms developed for image classification applications un-der a broad range of specific applications. Sometimes, it mayincreasethequalityofclassificationresultswhenmultiplemethods(algorithms)arejointlyemployed.Forexample, Loand Choi (2004) proposed a hybrid method that incorporatedthe advantages of supervised and unsupervised approaches aswell as hard and soft classifications for mapping the land coverin Atlanta Metropolitan Area using Landsat 7 ETM+ data. How-ever, cautions should be usually exercised when applying im-proved classifiers because these methods were often designedand developed under specific challenges to solve unique prob-lems. Moreover, discrimination of vegetation species from sin-gleimageryisonlyachievablewhereacombinationofleafchemistry, structureandmoisturecontentculminatestoforma unique spectral signature. Thus, imagery classification relieson successful extraction of pure spectral signature for each spe-cies, which is often dictated by the spatial resolution of the ob-servingsensorandthetimingofobservation(AsnerandHeidebrecht 2002; Varshney and Arora 2004). In short, searchfor improved image classification algorithms is still a hot field inthe remote sensing applications because there are no superclassificationmethodsthatcouldapplyuniversally.

Hyperspectralimageryanddatafusion

Inrecentyears,moreadvancedmethodsreflectingthelatestre-mote sensing techniques used invegetationmappingare seen inliterature.Amongthem,theapplicationsofhyperspectralim-ageryandmultipleimageryfusiontoextractvegetationcoverarera pidlydevelopedandthusdeserveourspecialattention.

Vegetationmappingfromhyperspectralimagery

Ratherthanusingmultispectralimagery,vegetation extrac-tionfromhyperspectralimageryisincreasinglystudiedre-cently.Compared with multispectral imagery that only hasa dozen of spectral bands, hyperspectral imagery includes hun-dreds of spectral bands. Hyperspectral sensors are well suitedfor vegetation studies as reflectance/absorption spectral signa-tures from individual species as well as more complex mixed-pixel communities can be better differentiated from the muchwider spectral bands of hyperspectral imagery (Varshney andArora2004).Forexample,thehyperspectralimageryfromAVIRI Sis commonly used in the realm of earth remote sens-ing. AVIRIS is a unique optical sensor that delivers calibratedimages of the upwelling spectral radiance in 224 contiguousspectral channels (bands) with the wavelengths ranging from400 to 2500 nm. The information within those bands can beutilized to identify, measure and monitor constituents of theearth’s surface (e.g. vegetation types) based on molecular ab-sorption and particle scattering signatures. One of the studiesusing AVIRIS imagery wasto classify salt marshes in China andin San Pablo Bay of California, USA (Li *et al.* 2005). The resultsweresatisfactoryconsideringthesuccessinclassifying twomain marsh vegetation species, *Spartina* and *Salicornia*, whichcovered 93.8% of the total marsh, although further work wasrequired to correct the false detection of other marsh vegeta-tion species. A similar work was also conducted by Rosso *et al.*(2005) in the study of the structure of wetlands in San Fran-ciscoBayofCaliforniabymonitoringvegetationdynamicsaimed at proposing sustainable management of wetland eco-systems. Hyperspectral data acquired by the Hyperion instru-mentonboardtheEarthObserving-1(EO-1)satellitewereevaluatedforthediscriminationoffiveimportantBraziliansugarcanevarieties(Galvâo*etal.*2005).Theresultsshowedthat the five Brazilian sugarcane varieties were discriminatedusingEO-1Hyperiondata,implyingthathyperspectralimag-ery is capable of separating plant species, which may be verydifficultbyusingmultispectralimages.

Althoughthegeneralprocedures(preprocessingandclassi-fication)forhyperspectralimagesarethesameasthoserequired for multispectral images, the processing of hyperspec-tral data remains a challenge. Specialized, cost effective andcomputationally efficient procedures are required to processhundreds of bands (Varshney and Arora 2004). To extract veg-etation communities or species from hyperspectral imagery,a set of signature libraries of vegetation are usually required(Xavier*etal.*2006).Forcertainapplications,thevegetationli-brariesforparticularvegetationcommunitiesorspeciesmight be already available. However, for most cases, the spectral sig-naturelibraryisestablishedusinggroundtruthdatawithhyperspectral data or through spectrometers. As such, vegeta-tionmappingusinghyperspectralimagerymustbewelldesigned to collect synchronous field data for creating imagerysignatures.

Vegetationmappingthroughimagefusion

The information provided by each individual sensor may beincomplete, inconsistent and imprecise for a given application.Image fusion of remotely sensed data with multiple spatialresolutionsisaneffectivetechniquethathasagoodpotential forimprovingvegetationclassification.Itisimportantforaccurate vegetation mapping to efficiently integrate remotesensinginformationwithdifferenttemporal,spectralandspatialresolutionsthroughimagefusion.Therearemanystudies focusing on the development of new fusion algorithms(AmarsaikhanandDouglas2004;Zhang2004;Zhuand Tateishi2006).Forexample,inthestudyoffusionforhigh-resolutionpanchromaticandlow-resolutionmulti-spectral remote sensing images, Li *et al.* (2006) proposed a fre-quencybuffermodeltoovercomethedifficultyofidentifyinghigh-frequency components of panchromatic images and low-frequencycomponentsofmultispectralimages.Basedonthestatistical fusion of multi-temporal satellite images, Zhu andTateishi (2006) developed a new temporal fusion classificationmodel to study land cover classification and verified its im-proved performance over the conventional methods. Behnia(2005) compared four frequently adopted image fusion algo-rithms,namelyprinciplecomponenttransform,broveytrans-form, smoothing filter-based intensity modulation and HSIandconcludedthateachofthemimprovesthespatialresolu-tioneffectivelybutdistortstheoriginalspectralsignaturestocertain degrees. To solve the color distortion associated withsome existing techniques, Wu *et al.* (2005) developed an en-hancement color normalized algorithm to merge lower spatialresolution multispectral images with a higher spatial resolu-tion panchromatic image. Rather than designing new fusionalgorithms, Colditz *et al.* (2006) tested various image fusionmethods to study their impacts on land cover classification ac-curacies ranging from common techniques like brovey, hue–saturation–valuetransformandprincipalcomponentanalysisto more complex approaches like adaptive image fusion, multi-sensor multi-resolution image fusion technique and wavelettransformation.Inbrief,imagefusionopensanewwaytoex-tract high accuracy vegetation covers by integrating remotesensing images from different sensors. However, the chal-lenges of fusion strategy (including developing new fusionalgorithms)stillrequirefurtherstudies.

Resultevaluation

Theproductsofvegetationmappingderivedfromremotesensedimagesshouldbeobjectivelyverifiedand communicatedtouserssothattheycanmakeinformeddeci-sions on whether and how the products can be used. Resultevaluation, a procedure also called accuracy assessment, is of-tenemployedtodeterminethedegreeof‘correctness’oftheclassified vegetation groups compared to the actual ones. Avegetation map derived from image classification is consideredaccurate if it provides a true representation of the region it portrays(Foody2002;Weber2006).Foursignificantstageshavebeen witnessed in accuracy assessment methods (Congalton1994). Accuracy assessment in the first stage was done by visualinspectionofderivedmaps.Thismethodisdeemedtobehighly subjective and often not accurate. The second stageused a more objective method by which comparisons of theareaextentsoftheclassesinthederivedthematicmaps(e.g.thepercentageofaspecificvegetationgroupinarea)weremade with the corresponding extents on ground or in otherreference dataset. However, there is a major problem with thisnon-site-specific approach since the correct proportions of veg-etation groups do not necessarily mean the correct locations atwhich they locate. In the third stage, the accuracy metrics werebuilt on a comparison of the class labels in the thematic mapwith the ground data for the same locations. Measures such asthe percentages of cases correctly (and wrongly) classifiedwere used to evaluate the classification accuracy. The accuracyassessment at the fourth stage made further refinements onthe basis of the third stage. The obvious characteristic of thisstage is the wide use of the confusion or error matrix, whichdescribesthefitnessbetweenthederivedclassesandthereferencedatathroughusingthemeasureslikeoverallaccuracyand kappa coefficient. Additionally, a variety of other measuresisalsoavailableorcanbederivedfromtheerrormatrix.Forexample,theaccuracyofindividualclassescanbederivediftheuserisinterestedinspecificvegetationgroups.

Althoughitisagreedthataccuracyassessmentisimportant to qualify the result of image classification, it is probably impossibletospecifyasingle,all-purposemeasureforassessingclassificationaccuracy.Forexample,theconfusionmatrixandits derived measures of accuracy may seem reasonable and fea-sible. However, they may not be applicable under some circumstances,especiallyinvegetationmappingatcoarsescales(Cingolani*etal.*2004).Oneoftheproblemscausedby the pixel-based confusion matrix evaluation is that a pixelat a coarse resolution may include several vegetation types. Asshown in Fig. 3, a pixel in imagery represents a composite ofthreevegetationclasses(class*A*,*B*and*C*).Clearly,theeclipselocated in the center of the pixel may be the sampling area.Since it is impractical to sample the whole pixel at a large-scalemapping, this pixel would most likely be labeled with class *B* inimage classification considering its percentage of the occupiedarea.Therefore,thevegetationclassbetweenthederived(class*B*) and the referenced (class *A*) will not match and this mis-match will introduce classification errors. In this case, thenon-site-specific accuracy measures may be more suitable ifnotforthelimitationmentionedpreviously.Moreover,ratherthanusingfieldsamplestotesttheclassificationaccuracy,

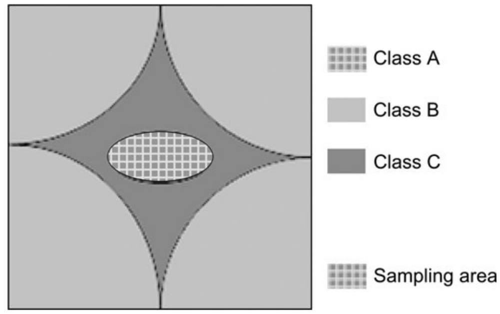

Figure 3 illustration for pixel-based accuracy assessment at coarsescale. The envelope square represents a pixel in imagery. Here problemoccurs:ground'true'vegetationclassis*A*,butclassifiedresultforthepixel, if correctly classified, would be labeled with *B*. This would lead toa mismatch between ground referenced data and classified result,which isvery typical in pixel-based accuracy assessment especiallyatlarge-scalevegetationmapping.

a widely accepted practice is to use finer resolution satellitedatatoassesscoarserresolutionproducts(Cihlar*etal.*2003),althoughthehigh-resolutiondataarethemselvessubjecttointerpretationandpossibleerrors(DefriesandTownshend 1999). The result evaluating for image classificationstillremainsahotdebatingtopictoday(Foody2002).

Conclusions

Thispapercoveredawidearrayoftopicsinvegetationclassi-fication using remote sensing imagery. First, a range of remotesensing sensors and their applications in vegetation mappingwere introduced to facilitate the selection of right remote sensingproductsforspecificapplications.Second,thetechniquesof image preprocessing and various classification methods (traditionalandimproved)werediscussedonhowtoextractveg-etation features from remote sensing images. Particularly, theextractionofvegetationcoverthroughtheapplicationofhyperspectralimageryandimagefusionwasdiscussed.Third,asectionwasdedicatedtothediscussionofresultevaluation(accuracy assessment) of image classification. Although thecoverage of topics was not inclusive, and not all possible prob-lems were addressed, the basic steps, principles, techniquesandmethodsofmappingvegetationcoverfromremote sens-ing imagery were discussed and the supporting referenceswereprovided.

In short, remote sensing images are key data sources forearth monitoring programs considering the great advantagesthattheyhave(NordbergandEvertson2003).Forinstance,itismoreeasilyobtainabletoproduceandupdatevegetationinventoriesoverlargeregionsifaidedbysatelliteimageryandappropriate imagery analysis. A growing number of studieshave examined a wide variety of vegetative phenomena (including mapping vegetation cover) by using remote senseddata (Duchemin *et al.* 1999; Geerken *et al.* 2005; Nerry *et al.*1998;Xavier*etal.*2006).However,althoughremotesensing technology has tremendous advantages over traditional meth-odsinvegetationmapping,weshouldhaveaclearunder-standingofitslimitations.AsstatedbyRapp*et al.* (2005),three questions should be asked when using the results of veg-etation mapping from remote sensing imagery: how well thechosen classification system represents actual vegetation com-munitycomposition,howeffectivelyimagesfromremotesensing capture the distinguishing features of each mappingunitwithintheclassificationandhow well these mappingunitsare delineated by photointerpreters. In other word,a well-fit vegetation classification system should be carefullydesigned according to the objective of studies in order to betterrepresentactualvegetationcommunitycompositions.Morespecifically, the following points should be taken into consid-eration when selecting a right vegetation classification systemfor better classification accuracy (Rapp *et al.* 2005): (i) refiningclass definitions to decrease ambiguity, (ii) adding new classesto more adequately describe the complexity of local vegetationpatternsand(iii)usingahigherlevelofclassification.

Furthermore,becauseoftheselimitations,theto-be-classifiedvegetationtypes,categorizedbyphysiognomicclassificationsystems(Dansereau1962),floristicclassificationsystems(Salovaara *et al.* 2005; Thenkabail *et al.* 2003) or site-orientedvegetation classification systems (Degraaf and Chadwick 1984;Harms *et al.* 2001), must produce distinct spectral signatures sothat the remote sensed images could be differentiated. How-ever,thisisnotalwaystrueinmanycases,especiallywhena study area is covered by vegetations of complex forms or dif-ferent stages, which result in similar spectral responses amongdifferent vegetation groups or generate spectral variations forthesamevegetationgroup(Sha*etal.*2008).Difficultiesorchallengesareoftenencounteredtomapvegetation undersuch circumstances. One solution is to adopt more advancedimageclassificationmethodsuchas sub-pixel analysis (Leeand Lathrop 2005). Another way is to choose higher resolu-tions of imagery acquired by the right remote sensing sensorsso as to increase the distinguishable possibility in image clas-sification (Cingolani *et al.* 2004). Nevertheless, higher resolu-tionsofimagerywillmostlikelyincreasethecost.

Although there are some standard methods for image pre-processing, there are no super image classifiers that can be uni-formly applicable to all applications. Thus, it is a challengingtask,aswellasahotresearchtopic,toapplyeffectiveclassifiersortodevelopnewpowerfulclassifierssuitableforspecificapplications. Moreover, ancillary data, including field samples,topographicalfeatures,environmentalcharacteristics andother digital (geographic information system) data layers, havebeen proved very helpful to get a more satisfactory result orincrease classification accuracy. It is advisable to keep in mindthatthetechnicalimprovements(designingmoreadvancedclassifiersoracquiringhigh-resolutionimagery,etc.)cannotsolve all problems that are encountered during vegetation ex-tractionfromremotesenseddatabutwillimprovetheresults.It is especially difficult to map vegetations over large areas suchasatcontinentalorglobalscales.Commonly,vegetationcover

mapsatlargescalesarecompositionsofmanymapsfromdif-ferentsourcesoveralongtime.AsstatedbyWhite(1983),forexample, the UNESCO/AETFAT/UNSO vegetation of Africa ata continent scale is the compilation of many national or localmapsovera15-yearperiod.Itisnotsurprisingthattheoverallaccuracyoftheproductisnotsatisfactoryasthosenationalorlocal maps are based on heterogeneous conceptions of vegeta-tion classification systems and produced at different periods.Therefore, it is very preferable to conduct vegetation classifi-cation using the data acquired from the same sources and atthe same period and applying the same processing methodsfortheentireregion.Thelackofsuchconsistentandidenticaldata (mainly remote sensed data and the reference data) forlarge regions often limits the production of vegetation mapswithgoodquality.

References

Al-Bakri JT, Taylor JC (2003) Application of NOAA AVHRR for mon-itoringvegetationconditionsandbiomassinJordan.*JAridEnviron*54:579–93.

Amarsaikhan D, Douglas T (2004) Data fusion and multisource imageclassification.*IntJRemoteSens*25:3529–39.

AsnerGP,HeidebrechtKB(2002)Spectralunmixingofvegetation,soilanddrycarboncoverinaridregions:comparingmultispectralandhyperspectralobservations.*IntJRemoteSens*23:3939–58.

AsrarG,FuchM,KanemasuET,etal.(1984)Estimatingabsorbedpho-tosynthetic radiation and leaf area index from spectral reflectance inwheat.*AgronJ*76:300–6.

Bagan H, Yang Y, Ma J, et al. (2005) Land cover classification fromMODIS EVI times-series data using SOM neural network. *Int J Re-moteSens*26:4999–5012.

Barbosa HA, Huete AR, Baethgen WE (2006) A 20-year study of NDVIvariabilityovertheNortheastRegionofBrazil.*JAridEnviron*67: 288–307.

Beeri O, Phillips R, Hendrickson J, et al. (2007) Estimating foragequantity and quality using aerial hyperspectral imagery for north-ernmixed-grassprairie. *RemoteSensEnviron*110:216–25.

Behnia P (2005) Comparison between four methods for data fusionofETM+ multispectralandpanimages.*Geo-SpatialInfSci*8:98–103.

Berberoglu S, Lloyd CD, Atkinson PM, Curran PJ (2000) The integra-tionofspectralandtexturalinformationusingneuralnetworksforlandcovermappingintheMediterranean.*Comput.Geosci*26:385–396.

CabralAIR,MartinsE,BartholoméÉ,etal.(2006)Alandcovermapof southernhemisphereAfricabasedonSPOT-4vegetationdata.*IntJRemoteSens*27:1053–74.

Cakir HI, Khorram S, Nelson SAC (2006) Correspondence analysis fordetectinglandcoverchange.*RemoteSensEnviron*102:306–17.

ČernáL,ChytrýM(2005)Supervisedclassificationofplantcommu-nitieswithartificialneuralnetworks.*JVegSci*16:407–14.