ISSN 2518-170X (Online)
ISSN 2224-5278 (Print)

NEWS OF THE NATIONAL ACADEMY OF SCIENCES OF THE REPUBLIC OF KAZAKHSTAN, SERIES OF GEOLOGY AND TECHNICAL SCIENCES

№2
2026

ISSN 2518-170X (Online)
ISSN 2224-5278 (Print)

CENTRAL ASIAN ACADEMIC
RESEARCH CENTER

N E W S
OF THE NATIONAL ACADEMY OF SCIENCES OF THE REPUBLIC OF KAZAKHSTAN, SERIES OF GEOLOGY AND TECHNICAL SCIENCES

2 (476)

MARCH – APRIL 2026

THE JOURNAL WAS FOUNDED IN 1940

PUBLISHED 6 TIMES A YEAR

ALMATY, 2026

The scientific journal News of the National Academy of Sciences of the Republic of Kazakhstan, Series of Geology and Technical Sciences has been indexed in the international abstract and citation database Scopus since 2016 and demonstrates stable bibliometric performance.

The journal is also included in the Emerging Sources Citation Index (ESCI) of the Web of Science platform (Clarivate Analytics, since 2018).

Indexing in ESCI confirms the journal's compliance with international standards of scientific peer review and editorial ethics and is considered by Clarivate Analytics as part of the evaluation process for potential inclusion in the Science Citation Index Expanded (SCIE), Social Sciences Citation Index (SSCI), and Arts & Humanities Citation Index (AHCI).

Indexing in Scopus and Web of Science ensures high international visibility of publications, promotes citation growth, and reflects the editorial board's commitment to publishing relevant, original, and scientifically significant research in the fields of geology and technical sciences.

«Қазақстан Республикасы Ұлттық ғылым академиясының Хабарлары. Геология және техникалық ғылымдар сериясы» ғылыми журналы 2016 жылдан бастап халықаралық рефеpативтік және ғылымиметриялық Scopus дерекқорында индекстеледі және тұрақты библиометриялық көрсеткіштерді көрсетіп келеді.

Сонымен қатар журнал Web of Science платформасының (Clarivate Analytics, 2018) халықаралық рефеpативтік және наукометриялық дерекқоры Emerging Sources Citation Index (ESCI) тізіміне енгізілген.

ESCI дерекқорында индекстелуі журналдың халықаралық ғылыми рецензиялау талаптары мен редакциялық этика стандарттарына сәйкестігін растайды, сондай-ақ Clarivate Analytics компаниясы тарапынан басылымды Science Citation Index Expanded (SCIE), Social Sciences Citation Index (SSCI) және Arts & Humanities Citation Index (AHCI) дерекқорларына енгізу қарастырылуда.

Scopus және Web of Science дерекқорларында индекстелуі жарияланымдардың халықаралық деңгейде жоғары сұранысқа ие болуын қамтамасыз етеді, олардың дәйексөз алу көрсеткіштерінің артуына ықпал етеді және редакциялық алқаның геология мен техникалық ғылымдар саласындағы өзекті, бірегей және ғылыми тұрғыдан маңызды зерттеулерді жариялауға ұмтылысын айқындайды.

Научный журнал «News of the National Academy of Sciences of the Republic of Kazakhstan, Series of Geology and Technical Sciences» с 2016 года индексируется в международной реферативной и наукометрической базе данных Scopus и демонстрирует стабильные библиометрические показатели.

Журнал также включён в международную реферативную и наукометрическую базу данных Emerging Sources Citation Index (ESCI) платформы Web of Science (Clarivate Analytics, 2018).

Индексирование в ESCI подтверждает соответствие журнала международным стандартам научного рецензирования и редакционной этики, а также рассматривается компанией Clarivate Analytics в рамках дальнейшего включения издания в Science Citation Index Expanded (SCIE), Social Sciences Citation Index (SSCI) и Arts & Humanities Citation Index (AHCI).

Индексирование в Scopus и Web of Science обеспечивает высокую международную востребованность публикаций, способствует росту цитируемости и подтверждает стремление редакционной коллегии публиковать актуальные, оригинальные и научно значимые исследования в области геологии и технических наук.

EDITOR-IN-CHIEF

ZHURINOV Murat Zhurinovich, Doctor of Chemical Sciences, Professor, Academician of IAAS and NAS RK, General Director of the Research Institute of Petroleum Refining and Petrochemicals (Almaty, Kazakhstan), https://www.scopus.com/authid/detail.uri?authorId=6602177960; https://www.webofscience.com/wos/author/record/2017489

DEPUTY EDITOR-IN-CHIEF

ABSADYKOV Bakhyt Narikbayevich, Doctor of Technical Sciences, Professor, Academician of NAS RK, Satbayev University (Almaty, Kazakhstan), https://www.scopus.com/authid/detail.uri?authorId=6504694468; https://www.webofscience.com/wos/author/record/2411827

EDITORIAL BOARD:

ABSAMETOV Malis Kudysovich, Doctor of Geological and Mineralogical Sciences, Professor, Academician of NAS RK, Director of the U.M. Akhmedsafin Institute of Hydrogeology and Geoecology (Almaty, Kazakhstan), https://www.scopus.com/authid/detail.uri?authorId=56955769200; https://www.webofscience.com/wos/author/record/1937883

ZHOLTAEV Geroy Zholtaevich, Doctor of Geological and Mineralogical Sciences, Professor, Honorary Academician of NAS RK (Almaty, Kazakhstan), https://www.scopus.com/authid/detail.uri?authorId=57112610200; https://www.webofscience.com/wos/author/record/1939201

SNOW Daniel, PhD, Associate Professor, Director, Aquatic Sciences Laboratory, University of Nebraska (Nebraska, USA), https://www.scopus.com/authid/detail.uri?authorId=7103259215; https://www.webofscience.com/wos/author/record/1429613

SELTMANN Reimar, PhD, Head of Petrology and Mineral Deposits Research in the Earth Sciences Department, Natural History Museum (London, Great Britain), https://www.scopus.com/authid/detail.uri?authorId=55883084800; https://www.webofscience.com/wos/author/record/1048681

PANFILOV Mikhail Borisovich, Doctor of Technical Sciences, Professor at the University of Nancy (Nancy, France), https://www.scopus.com/authid/detail.uri?authorId=7003436752; https://www.webofscience.com/wos/author/record/1230499

SHEN Ping, PhD, Deputy Director of the Mining Geology Committee of the Chinese Geological Society, Member of the American Association of Economic Geologists (Beijing, China), https://www.scopus.com/authid/detail.uri?authorId=57202873965; https://www.webofscience.com/wos/author/record/1753209

FISCHER Axel, PhD, Associate Professor, Technical University of Dresden (Dresden, Germany), https://www.scopus.com/authid/detail.uri?authorId=35738572100; https://www.webofscience.com/wos/author/record/2085986

AGABEKOV Vladimir Enokovich, Doctor of Chemical Sciences, Academician of NAS of Belarus, Honorary Director of the Institute of Chemistry of New Materials (Minsk, Belarus), https://www.scopus.com/authid/detail.uri?authorId=7004624845

CATALIN Stefan, PhD, Associate Professor, Technical University of Dresden (Dresden, Germany), https://www.scopus.com/authid/detail.uri?authorId=35203904500; https://www.webofscience.com/wos/author/record/1309251

JAY Sagin, PhD, Associate Professor, Nazarbayev University (Astana, Kazakhstan), https://www.scopus.com/authid/detail.uri?authorId=57204467637; https://www.webofscience.com/wos/author/record/907886

FRATTINI Paolo, PhD, Associate Professor, University of Milano - Bicocca (Milan, Italy), https://www.scopus.com/authid/detail.uri?authorId=56538922400

NURPEISOVA Marzhan Baysanovna, Doctor of Technical Sciences, Professor of Satbayev University (Almaty, Kazakhstan), https://www.scopus.com/authid/detail.uri?authorId=57202218883; https://www.webofscience.com/wos/author/record/AAD-1173-2019

RATOV Boranbay Tovbasarovich, Doctor of Technical Sciences, Professor, Head of the Department of Geophysics and Seismology, Satbayev University (Almaty, Kazakhstan), https://www.scopus.com/authid/detail.uri?authorId=55927684100; https://www.webofscience.com/wos/author/record/1993614

RONNY Berndtsson, Professor, Director of the Centre for Advanced Middle Eastern Studies, Lund University (Lund, Sweden), https://www.scopus.com/authid/detail.uri?authorId=7005388716; https://www.webofscience.com/wos/author/record/1324908

MIRLAS Vladimir, PhD, Professor, Eastern R&D Center, Ariel University (Ariel, Israel), https://www.scopus.com/authid/detail.uri?authorId=8610969300; https://www.webofscience.com/wos/author/record/53680261

News of the National Academy of Sciences of the Republic of Kazakhstan. Series of geology and technology sciences.
ISSN 2518-170X (Online),
ISSN 2224-5278 (Print)
Owner: «Central Asian Academic Research Center» LLP (Almaty).
The certificate of registration of a periodical printed publication in the Committee of information of the Ministry of Information and Communications of the Republic of Kazakhstan № KZ50VPY00121155, issued on 05.06.2025
Thematic scope: *geology, hydrogeology, geography, mining and chemical technologies of oil, gas and metals*
Periodicity: 6 times a year.
http://www.geolog-technical.kz/index.php/en/

© «Central Asian Academic Research Center» LLP, 2026.

БАС РЕДАКТОР

ЖҰРЫНОВ Мұрат Жұрынұлы, химия ғылымдарының докторы, профессор, ХҒАҚ және ҚР ҰҒА академигі, Мұнай өңдеу және мұнай-химиясы ғылыми-зерттеу институтының бас директоры (Алматы, Қазақстан), https://www.scopus.com/authid/detail.uri?authorId=6602177960; https://www.webofscience.com/wos/author/record/2017489

БАС РЕДАКТОРДЫҢ ОРЫНБАСАРЫ:

АБСАДЫҚОВ Бақыт Нәрікбайұлы, техника ғылымдарының докторы, профессор, ҚР ҰҒА академигі, Қ.И. Сәтбаев атындағы Қазақ ұлттық техникалық зерттеу университеті (Алматы, Қазақстан), https://www.scopus.com/authid/detail.uri?authorId=6504694468; https://www.webofscience.com/wos/author/record/2411827

РЕДАКЦИЯ АЛҚАСЫ:

ӘБСӘМЕТОВ Мәліс Құдысұлы, геология-минералогия ғылымдарының докторы, профессор, ҚР ҰҒА академигі, У.М. Ахмедсафин атындағы Гидрогеология және геоэкология институтының директоры (Алматы, Қазақстан), https://www.scopus.com/authid/detail.uri?authorId=56955769200; https://www.webofscience.com/wos/author/record/1937883

ЖОЛТАЕВ Герой Жолтайұлы, геология-минералогия ғылымдарының докторы, профессор, ҚР ҰҒА құрметті академигі (Алматы, Қазақстан), https://www.scopus.com/authid/detail.uri?authorId=57112610200; https://www.webofscience.com/wos/author/record/1939201

СНОУ Дэниел, PhD, қауымдастырылған профессор, Небраска университетінің Су ғылымдары зертханасының директоры (Небраска, АҚШ), https://www.scopus.com/authid/detail.uri?authorId=7103259215; https://www.webofscience.com/wos/author/record/1429613

ЗЕЛЬТМАНН Раймар, PhD, Жер туралы ғылымдар бөлімінің петрология және пайдалы қазбалар кен орындары саласындағы зерттеулерінің жетекшісі, Табиғи тарих мұражайы (Лондон, Ұлыбритания), https://www.scopus.com/authid/detail.uri?authorId=55883084800; https://www.webofscience.com/wos/author/record/ 1048681

ПАНФИЛОВ Михаил Борисович, техника ғылымдарының докторы, Нанси университетінің профессоры (Нанси, Франция), https://www.scopus.com/authid/detail.uri?authorId=7003436752; https://www.webofscience.com/wos/author/record/1230499

ШЕН Пин, PhD, Қытай геологиялық қоғамының Тау-кен геологиясы комитеті директорының орынбасары, Американдық экономикалық геологтар қауымдастығының мүшесі (Бейжің, Қытай), https://www.scopus.com/authid/detail.uri?authorId=57202873965; https://www.webofscience.com/wos/author/record/ 1753209

ФИШЕР Аксель, PhD, қауымдастырылған профессор, Дрезден техникалық университеті (Дрезден, Германия), https://www.scopus.com/authid/detail.uri?authorId=35738572100; https://www.webofscience.com/wos/author/record/2085986

АГАБЕКОВ Владимир Енокович, химия ғылымдарының докторы, Беларусь ҰҒА академигі, Жаңа материалдар химиясы институтының құрметті директоры (Минск, Беларусь), https://www.scopus.com/authid/detail.uri?authorId=7004624845

КАТАЛИН Стефан, PhD, қауымдастырылған профессор, Дрезден Техникалық университеті (Дрезден, Германия), https://www.scopus.com/authid/detail.uri?authorId=35203904500; https://www.webofscience.com/wos/author/record/1309251

САҒЫНТАЕВ Жанай, PhD, қауымдастырылған профессор, Назарбаев университеті (Астана, Қазақстан), https://www.scopus.com/authid/detail.uri?authorId=57204467637; https://www.webofscience.com/wos/author/record/907886

ФРАТТИНИ Паоло, PhD, қауымдастырылған профессор, Бикокк Милан университеті (Милан, Италия), https://www.scopus.com/authid/detail.uri?authorId=56538922400

НҰРПЕЙІСОВА Маржан Байсанқызы, техника ғылымдарының докторы, Қ.И. Сәтбаев атындағы Қазақ ұлттық техникалық зерттеу университетінің профессоры (Алматы, Қазақстан), https://www.scopus.com/authid/detail.uri?authorId=57202218883; https://www.webofscience.com/wos/author/record/AAD-1173-2019

РАТОВ Боранбай Товбасарович, техника ғылымдарының докторы, профессор, «Геофизика және сейсмология» кафедрасының меңгерушісі, Қ.И. Сәтбаев атындағы Қазақ ұлттық техникалық зерттеу университеті (Алматы, Қазақстан), https://www.scopus.com/authid/detail.uri?authorId=55927684100; https://www.webofscience.com/wos/author/record/1993614

РОННИ Берндтссон, профессор, Таяу Шығысты заманауи зерттеу орталығының директоры, Лунд университеті (Лунд, Швеция), https://www.scopus.com/authid/detail.uri?authorId=7005388716; https://www.webofscience.com/wos/author/record/1324908

МИРЛАС Владимир, PhD, профессор, Ариэль университетінің Шығыс ғылыми-зерттеу орталығы (Ариэль, Израиль), https://www.scopus.com/authid/detail.uri?authorId=8610969300; https://www.webofscience.com/wos/author/record/53680261

News of the National Academy of Sciences of the Republic of Kazakhstan. Series of geology and technology sciences.
ISSN 2518-170X (Online),
ISSN 2224-5278 (Print)
Меншіктеуші: «Орталық Азия академиялық ғылыми орталығы» ЖШС (Алматы қ.).
Қазақстан Республикасының Ақпарат және коммуникациялар министрлігінің Ақпарат комитетінде 05.06.2025 ж. берілген № KZ50VPY00121155 мерзімдік басылым тіркеуіне қойылу туралы куәлік.
Тақырыптық бағыты: *геология, гидрогеология, география, тау-кен ісі, мұнай, газ және металдардың химиялық технологиялары*
Мерзімділігі: жылына 6 рет.
http://www.geolog-technical.kz/index.php/en/

© «Орталық Азия академиялық ғылыми орталығы» ЖШС, 2026,

ГЛАВНЫЙ РЕДАКТОР

ЖУРИНОВ Мурат Журинович, доктор химических наук, профессор, академик МААН и НАН РК, Генеральный директор НИИ нефтепереработки и нефтехимии (Алматы, Казахстан), https://www.scopus.com/authid/detail.uri?authorId=6602177960; https://www.webofscience.com/wos/author/record/2017489

ЗАМЕСТИТЕЛЬ ГЛАВНОГО РЕДАКТОРА

АБСАДЫКОВ Бахыт Нарикбаевич, доктор технических наук, профессор, академик НАН РК, Казахский национальный исследовательский технический университет им. К.И. Сатпаева (Алматы, Казахстан), https://www.scopus.com/authid/detail.uri?authorId=6504694468; https://www.webofscience.com/wos/author/record/2411827

РЕДАКЦИОННАЯ КОЛЛЕГИЯ:

АБСАМЕТОВ Малис Кудысович, доктор геолого-минералогических наук, профессор, академик НАН РК, директор Института гидрогеологии и геоэкологии им. У.М. Ахмедсафина (Алматы, Казахстан), https://www.scopus.com/authid/detail.uri?authorId=56955769200; https://www.webofscience.com/wos/author/record/1937883

ЖОЛТАЕВ Герой Жолтаевич, доктор геолого-минералогических наук, профессор, почетный академик НАН РК (Алматы, Казахстан), https://www.scopus.com/authid/detail.uri?authorId=57112610200; https://www.webofscience.com/wos/author/record/1939201

СНОУ Дэниел, PhD, ассоциированный профессор, директор Лаборатории водных наук Университета Небраски (Небраска, США), https://www.scopus.com/authid/detail.uri?authorId=7103259215; https://www.webofscience.com/wos/author/record/1429613

ЗЕЛЬТМАНН Раймар, PhD, руководитель исследований в области петрологии и месторождений полезных ископаемых в Отделе наук о Земле Музея естественной истории (Лондон, Великобритания), https://www.scopus.com/authid/detail.uri?authorId=55883084800; https://www.webofscience.com/wos/author/record/ 1048681

ПАНФИЛОВ Михаил Борисович, доктор технических наук, профессор Университета Нанси (Нанси, Франция), https://www.scopus.com/authid/detail.uri?authorId=7003436752; https://www.webofscience.com/wos/author/record/1230499

ШЕН Пин, PhD, заместитель директора Комитета по горной геологии Китайского геологического общества, член Американской ассоциации экономических геологов (Пекин, Китай), https://www.scopus.com/authid/detail.uri?authorId=57202873965; https://www.webofscience.com/wos/author/record/1753209

ФИШЕР Аксель, PhD, ассоциированный профессор, Технический университет Дрезден (Дрезден, Берлин), https://www.scopus.com/authid/detail.uri?authorId=35738572100; https://www.webofscience.com/wos/author/record/2085986

АГАБЕКОВ Владимир Енокович, доктор химических наук, академик НАН Беларуси, почетный директор Института химии новых материалов (Минск, Беларусь), https://www.scopus.com/authid/detail.uri?authorId=7004624845

КАТАЛИН Стефан, PhD, ассоциированный профессор, Технический университет Дрезден (Дрезден, Германия), https://www.scopus.com/authid/detail.uri?authorId=35203904500; https://www.webofscience.com/wos/author/record/ 1309251

САГИНТАЕВ Жанай, PhD, ассоциированный профессор, Назарбаев университет (Астана, Казахстан), https://www.scopus.com/authid/detail.uri?authorId=57204467637; https://www.webofscience.com/wos/author/record/907886

ФРАТТИНИ Паоло, PhD, ассоциированный профессор, Миланский университет Бикокк (Милан, Италия), https://www.scopus.com/authid/detail.uri?authorId=56538922400

НУРПЕИСОВА Маржан Байсановна, доктор технических наук, профессор Казахского национального исследовательского технического университета им. К.И. Сатпаева (Алматы, Казахстан), https://www.scopus.com/authid/detail.uri?authorId=57202218883; https://www.webofscience.com/wos/author/record/AAD-1173-2019

РАТОВ Боранбай Товбасарович, доктор технических наук, профессор, заведующий кафедрой «Геофизика и сейсмология», Казахский национальный исследовательский технический университет им. К.И. Сатпаева (Алматы, Казахстан), https://www.scopus.com/authid/detail.uri?authorId=55927684100; https://www.webofscience.com/wos/author/record/1993614

РОННИ Берндтссон, профессор, Директор Центра современных ближневосточных исследований, Лундский университет (Лунд, Швеция), https://www.scopus.com/authid/detail.uri?authorId=7005388716; https://www.webofscience.com/wos/author/record/1324908

МИРЛАС Владимир, PhD, профессор, Восточный научно-исследовательский центр, Университет Ариэля, (Ариэль, Израиль), https://www.scopus.com/authid/detail.uri?authorId=8610969300; https://www.webofscience.com/wos/author/record/53680261

News of the National Academy of Sciences of the Republic of Kazakhstan. Series of geology and technology sciences.
ISSN 2518-170X (Online),
ISSN 2224-5278 (Print)
Собственник: ТОО «Центрально-Азиатский академический научный центр» (г. Алматы).
Свидетельство о постановке на учет периодического печатного издания в Комитете информации Министерства информации и коммуникаций и Республики Казахстан № KZ50VPY00121155, выданное 05.06.2025 г.
Тематическая направленность: *геология, гидрогеология, география, горное дело и химические технологии нефти, газа и металлов*
Периодичность: 6 раз в год.
http://www.geolog-technical.kz/index.php/en/

© ТОО «Центрально-Азиатский академический научный центр», 2026.

CONTENTS

Abetov A.E., Seitzhanov A.K., Samenov Y.R., Zhassymbek S.A.
Machine learning and neural networks for lithofacies mapping and reservoir property evaluation of core samples....8

Aitkaliyev A.K., Pak Y.N., Kolmakov Y.V., Pak D.Y., Matishev T.V.
Application of the X-Ray radiometric method to improve the operational quality control of copper ores during geological testing....26

Altay Y.A., Karymsakova N.T., Fedorov A.V., Absadykov D.B., Ismagul G.K.
Predictive control of diagnostically significant parameters of acoustic emission using machine learning: new data....41

Astanakulov K.D., Kodirova M.G., Saydumarov B., Nersesyan D.V., Kurashkin S.O.
Resource potential of ecological and geological systems of allocated soil masses....58

Avazov Sh.B., Yodgorov Sh.I., Mukhammadkulov N.M., Aktamov B.U., Khayriddinov B.B.
Instrumental seismometric assessment of the impact of technogenic seismic vibrations on the structural stability of historical objects....74

Baskanbayeva D., Kalmaganbetov S., Sabirova L., Zholdybayeva G., Koptleuov K.
CFD analysis of screw compressor rotor geometry influence on gas compression efficiency in geology....92

Borotov A.N., Karshiev F.U., Igamberdiyev A.A., Grigoryan A.G., Sarigo N.V.
Ecological aspects of resource conservation in the development of mineral deposits......107

Gerasidi V.V., Lisachenko A.V., Apatenko A.S., Sevryugina N.S., Fomin A.Y.
Analysis of the application of non-destructive testing methods for assessing the technical condition of mining equipment motors based on vibration parameters....121

Hajiyeva A.Z., Ibrahimova L.P., Humbatova Sh.Y., Jafarova F.M.
Ecological processes of vertical landscape transformation and their manifestation in the natural landscapes of Nakhchivan....135

Jakiyayev D.K., Nussipali R.K.*, Malibekov A.K., Jakiyayev B.D., Zhashen S.Zh.
Statistical model of multi-cycle fatigue of steel structural elements under a complex non-uniform stress state....149

Jumatov Y.K., Tashbulatov S.B., Pushanov A.N., Kozenkova G.L., Yarygina I.V.
Technological substantiation of sustainable mining reclamation of disturbed lands in open pit operations....169

Kainenova T.S., Kosmbaeva G.T., Bissembayeva K.T., Otarbayeva A.T., Orazbek A.A.
Effectiveness of measures to regulate the development process at the Alibekmola field....185

Koishiyeva G.Zh., Yerimova A.Zh., Kurbaniyazov S.K., Agaidarova K.H., Abdraimova K.T.
Radiological properties and stratigraphic significance of glauconite-bearing formations: implications for paleoenvironments and geochemical zonation......................................203

Kondratiev V.V., Bryukhanova N.N., Kononenko R.V., Gladkikh V.A., Matasova I.Y.
Environmental and technological assessment of beneficiation tailings reprocessing based on mechanical activation and non-ferrous metals leaching...................................223

Kuldeyev Ye., Negmatov S., Nurpeissova M., Kirgizbaeva D., Donenbayeva N.
Geodynamic Polygon of the Zhilandy Ore Field: Results and Prospects.........................237

Madibekov A., Christian Opp., Karimov A., Ismukhanova L., Zhadi A. Regularities of distribution and accumulation factors of heavymetals in soils of the Zhetysu region (Kazakhstan)..253

Malikov G.I., Musayeva S.A., Mammadov K.S., Jabıyeva U.M., Jafarova K.V.
Effects of hydrocarbon fuel quality fluctuations on energy generation efficiency, economic viability, and environmental footprint..272

Narbaev M.T., Ismailova G.K., Narbaeva K.T., Burlibayeva D.M., Groll M.
Assessment of ecological and water management parameters of the Syrdarya River.......290

Nurmagambetov A.
On seismic hazard of Almaty and tectonic faults in the city...309

Permana A.P, Kasim M., Hutagalung R., Uno D.A.N., Sandi I.N.
petrographic, provenance, and tectonic setting of Dolokapa formation sandstone, North Gorontalo..319

Ratov B.T., Khomenko V.L., Yavorska O.O., Koroviaka Ye.A., Akhmetova N.S.
Analytical and structural justification of a wellhead sealing device for large-diameter drilling operations...335

Skrobala V.M., Popovych V.V., Kopylov V.P., Popovych N.P.
Comprehensive assessment of heavy metal pollution of a river within a large city..........355

Sunakbaeva D.Kh., Yuldashbek D.Kh., Aitekova K., Seitbayev K.Zh.
Monitoring heavy metals in soils and waters of the City of Turkestan: geoecological aspect..371

Zakirov M.M., Agzamova I.A., Ochilov G.E., Gulyamov G.D., Xudayberdiyev T.M.
Analysis of the results of changes in the gas and isotopic composition of groundwater during the period of earthquake preparation..385

Zhanbatyrov A.A., Tukhfatov Zh.K., Bektay E.K., Turisbekova G.S., Zhanbatyrov N.A.
Current state of potash ore development in the Caspian lowlands of the Republic of Kazakhstan: problems and solutions.. 399

NEWS OF THE NATIONAL ACADEMY OF SCIENCES OF THE REPUBLIC
OF KAZAKHSTAN, SERIES OF GEOLOGY AND TECHNICAL SCIENCES
ISSN 2224–5278
Volume 2.
Number 476 (2026), 8–25

https://doi.org/10.32014/2026.2518-170X.612

UDC: 550.8.053
IRSTI: 38.53.01

©Abetov A.E.[1], Seitzhanov A.K.[*2], Samenov Y.R.[1], Zhassymbek S.A.[1], 2026.
[1]Satbayev University, Almaty, Kazakhstan;
[2]Kazakh-British Technical University, Almaty, Kazakhstan.
[*]E-mail: ansar.seitzhanov.98@mail.ru

MACHINE LEARNING AND NEURAL NETWORKS FOR LITHOFACIES MAPPING AND RESERVOIR PROPERTY EVALUATION OF CORE SAMPLES

Abetov Auez — Doctor of Sciences in Geology and Mineralogy, Professor, Academician of the National Academy of Sciences of the Republic of Kazakhstan, Satbayev University, Almaty, Kazakhstan,
E-mail: abetov.auez@mail.ru, https://orcid.org/0000-0002-1866-7677;
Seitzhanov Ansar — PhD student, Kazakh-British Technical University, Almaty, Kazakhstan,
E-mail: ansar.seitzhanov.98@mail.ru, https://orcid.org/0009-0004-0700-2882;
Samenov Yernazar — Master student, Satbayev University, Almaty, Kazakhstan,
E-mail: samenov10@gmail.com, https://orcid.org/0000-0002-8299-5632;
Zhassymbek Safia — PhD student, Satbayev University, Almaty, Kazakhstan,
E-mail: sakonyaa94@gmail.com, https://orcid.org/0000-0002-5673-3612.

Abstract. *Relevance.* This study presents a machine learning (ML) approach for petrophysical core classification, applied to data from the southeastern margin of the Precaspian Depression - a geologically complex region characterized by heterogeneous reservoirs and diverse lithofacies. The Random Forest (RF) algorithm was chosen as the primary method due to its proven efficiency in handling nonlinear relationships and high-dimensional datasets, making it particularly suitable for complex geological environments. *Objective.* A Python-based workflow integrating Scikit-learn, Pandas, and Streamlit was developed to support the complete petrophysical analytical cycle — from data preprocessing to interactive visualization and interpretation. *Methods.* The RF model achieved 89% accuracy and an F1-score of 0.90 in lithotype classification (sandstones and siltstones). Porosity and permeability emerged as the most influential features, with the application of a logarithmic permeability scale significantly enhancing interpretability in low-permeability zones. Feature importance was rigorously quantified using the Gini index, enabling effective dataset optimization and dimensionality reduction. *Results and conclusions.* The model exhibited strong generalization capabilities, with over 90% test accuracy, and demonstrated robust resistance to overfitting, ensuring reliable performance on unseen data. The interactive web application further enhances usability by offering tools for hyperparameter tuning, feature importance analysis, and dynamic data visualization, supporting rapid and informed decision-making by petrophysicists.

In conclusion, the proposed ML framework offers a practical, scalable, and adaptable solution that significantly improves the speed, accuracy, and reliability of lithotype classification, making it a valuable tool for modern petrophysical workflows in geologically complex and heterogeneous reservoir settings.

Keywords: machine learning, Random Forest, rock properties, classification, Precaspian Depression

For citations: *Abetov A.E., Seitzhanov A.K., Samenov Y.R., Zhassymbek S.A. Machine Learning and Neural Networks for Lithofacies Mapping and Reservoir Property Evaluation of Core Samples. News of the National Academy of Sciences of the Republic of Kazakhstan, Series of Geology and Technical Sciences. 2026. No.2. Pp. 8–25. DOI: https://doi.org/10.32014/2026.2518-170X.612*

©Абетов А.Е.[1], Сейтжанов А.К.[*2], Саменов Е.Р.[1], Жасымбек С.А.[1], 2026.
[1]Сәтбаев университеті, Алматы, Қазақстан;
[2]Қазақстан-Британ техникалық университеті, Алматы, Қазақстан.
[*]E-mail: ansar.seitzhanov.98@mail.ru

ЛИТОФАЦИЯЛАРДЫ КАРТАЛАУ ЖӘНЕ КЕРН ҮЛГІЛЕРІНІҢ КОЛЛЕКТОРЛЫҚ ҚАСИЕТТЕРІН БАҒАЛАУ ҮШІН МАШИНАЛЫҚ ОҚЫТУ МЕН НЕЙРОНДЫҚ ЖЕЛІЛЕР

Абетов Ауэз — геология-минералогия ғылымдарының докторы, профессоры, Қазақстан Республикасы Ұлттық ғылым академиясының академигі, Сәтбаев университеті, Алматы, Қазақстан,
E-mail: abetov.auez@mail.ru, https://orcid.org/0000-0002-1866-7677;
Сейтжанов Ансар — PhD докторант, Қазақстан-Британ техникалық университеті, Алматы, Қазақстан,
E-mail: ansar.seitzhanov.98@mail.ru, https://orcid.org/0009-0004-0700-2882;
Саменов Ерназар — магистрант, Сәтбаев университеті, Алматы, Қазақстан,
E-mail: samenov10@gmail.com, https://orcid.org/0000-0002-8299-5632;
Жасымбек Сафия — PhD докторант, Сәтбаев университеті, Алматы, Қазақстан,
E-mail: sakonyaa94@gmail.com, https://orcid.org/0000-0002-5673-3612.

Аннотация. *Сәйкестік.* Бұл зерттеу петрофизикалық керндерді классификациялауға арналған машинамен оқыту (ML) тәсілін ұсынады, ол деректерді Прекаспий ойпаттарының оңтүстік-шығыс шеткі аймағынан алады - бұл геологиялық тұрғыдан күрделі, әртүрлі литофациялары бар және гетерогенді резервуарларымен сипатталатын аймақ. Негізгі әдіс ретінде Random Forest (RF) алгоритмі таңдалды, өйткені ол көпөлшемді деректер мен сызықтық емес тәуелділіктерді тиімді өңдеуге қабілетті, бұл күрделі геологиялық жағдайларға өте қолайлы. Сонымен қатар, RF моделі деректердегі шу мен шамадан тыс бейқұрылымдануды жеңуге мүмкіндік беріп, классификация нәтижелерінің тұрақтылығын қамтамасыз етеді. *Мақсат.* Толық петрофизикалық талдау циклін — деректерді алдын ала өңдеуден интерактивті визуализациялау мен интерпретациялауға дейін — қамтамасыз ету үшін Scikit-learn, Pandas және Streamlit кітапханаларын біріктіретін Python бағдарламалық кешені әзірленді. *Әдістері.* RF моделі литотиптерді (құмтастар мен сазтастар) классификациялауда 89% дәлдік және 0,90 F1-score көрсетті. Ең ықпалды ерекшеліктер ретінде пороздық және сүзгіштік анықталды, ал логарифмдік сүзгіштік шкаласын қолдану төмен сүзгішті аймақтарды интерпретациялауда нәтижелердің дәлдігін айтарлықтай арттырды. Ерекшеліктердің маңыздығы Gini индексі арқылы бағаланды, бұл деректер жиынтығын оңтайландыруға, артық ерекшеліктерді азайтуға және модельді жеңілдетуге мүмкіндік берді. *Нәтижелер мен қорытындылар.* Модель жаңа, көрмеген деректерде де сенімді жұмыс істей отырып, 90%-дан астам тесттік дәлдік көрсетті және переобучениеге төзімділігін дәлелдеді. Интерактивті веб-қосымша гиперпараметрлерді баптау, ерекшеліктердің маңыздығын талдау, динамикалық визуализация және интерактивті интерпретация құралдарын ұсынып, зерттеушілерге жылдам әрі ақпаратқа негізделген шешім қабылдауды қамтамасыз етеді.

Қорытындылай келе, ұсынылған ML-фреймворк литотиптерді классификациялаудың жылдамдығын, дәлдігін және сенімділігін айтарлықтай жақсартатын практикалық, масштабталатын және бейімделетін шешім болып табылады. Бұл тәсіл геологиялық күрделі және гетерогенді резервуарлық жүйелердегі қазіргі заманғы петрофизикалық жұмыс процестері үшін жоғары құнды құрал болып табылады және болашақта басқа күрделі геологиялық құрылымдарды талдау мен модельдеуге де қолданылуы мүмкін.

Түйін сөздер: машиналық оқыту, кездейсоқ орман, тау жыныстарының қасиеттері, жіктеу, Каспий маңы ойпаты

©Абетов А.Е.[1], Сейтжанов А.К.[*2], Саменов Е.Р.[1], Жасымбек С.А.[1], 2026.
[1]Satbayev University, Алматы, Казахстан;
[2]Казахстанско-Британский технический университет, Алматы, Казахстан.
[*]E-mail: ansar.seitzhanov.98@mail.ru

МАШИННОЕ ОБУЧЕНИЕ И НЕЙРОСЕТИ ДЛЯ КАРТИРОВАНИЯ ЛИТОФАЦИЙ И ОЦЕНКИ КОЛЛЕКТОРСКИХ СВОЙСТВ ОБРАЗЦОВ КЕРНА

Абетов Ауэз — доктор геолого-минералогических наук, профессор, академик Национальной Академии наук Республики Казахстан, Сатбаев университет, Алматы, Казахстан,

E-mail: abetov.auez@mail.ru, https://orcid.org/0000-0002-1866-7677;
Сейтжанов Ансар — PhD докторант, Казахстанско-Британский технический университет, Алматы, Казахстан,
E-mail: ansar.seitzhanov.98@mail.ru, https://orcid.org/0009-0004-0700-2882;
Саменов Ерназар — магистрант, Сатбаев университет, Алматы, Казахстан,
E-mail: samenov10@gmail.com, https://orcid.org/0000-0002-8299-5632;
Жасымбек София — PhD докторант, Сатбаев университет, Алматы, Казахстан,
E-mail: sakonyaa94@gmail.com, https://orcid.org/0000-0002-5673-3612.

Аннотация. *Актуальность.* В работе представлен подход к классификации образцов керна с использованием методов машинного обучения (ML), применённый к данным юго-восточной окраины Прикаспийская впадина - геологически сложного региона, характеризующегося гетерогенностью природных резервуаров, изменчивой литофациальной структурой и выраженной петрофизической неоднородностью. В качестве базовой модели выбран алгоритм случайного леса (Random Forest, RF), обладающий высокой эффективностью при обработке многомерных и нелинейных зависимостей, а также устойчивостью к шуму и переобучению, что обеспечивает надёжность результатов при анализе сложных геологических систем. *Цель исследования* - разработка программного комплекса на базе языка Python, интегрирующего библиотеки Scikit-learn, Pandas и Streamlit для поддержки полного цикла петрофизического анализа - от предварительной обработки данных до интерактивной визуализации и интерпретации. *Методы.* Для классификации литотипов (песчаники и алевролиты) использовалась модель Random Forest, достигшая точности 89% и значения F1-score 0,90. Наиболее значимыми параметрами оказались пористость и проницаемость, при этом применение логарифмического преобразования проницаемости позволило существенно улучшить интерпретацию низкопроницаемых зон. Оценка значимости признаков проводилась с использованием индекса Джини, что позволило оптимизировать набор входных переменных и снизить размерность модели без потери точности. *Результаты и выводы.* Модель продемонстрировала высокую обобщающую способность (более 90% точности на тестовой выборке) и устойчивость к переобучению. Разработанное интерактивное веб-приложение обеспечивает настройку гиперпараметров, анализ значимости признаков и динамическую визуализацию результатов, что существенно ускоряет процесс обработки и интерпретации данных. Таким образом, предложенный ML-фреймворк обеспечивает повышение скорости, точности и надёжности классификации литотипов и представляет собой масштабируемое и адаптируемое решение для современных петрофизических исследований в сложных и гетерогенных резервуарных системах с возможностью расширения на другие геологические объекты и интеграции в комплексные геолого-геофизические модели.

Ключевые слова: машинное обучение, случайный лес, свойства горных пород, классификация, Прикаспийская впадина

Introduction. At the present stage of development in Kazakhstan's oil and gas sector, a steady decline in hydrocarbon production from mature fields has become increasingly evident. This trend, which has persisted for several years, underscores an urgent imperative to expand the country's resource base. This issue is described in the State Program for Geological Exploration for 2021–2025. This Program based on the next approaches:

- research at existing fields to investigate geological and geophysical parameters;
- exploring new areas.

Digital transformation plays important role in modernizing the fundamental reconsidering of data processing and interpretation methods. Application of artificial intelligence (AI) and machine learning (ML) is particularly important, because these approaches help automate routine human works, increase accuracy and improve the reproducibility of the AI/ML models.

Intelligent algorithms unlock new opportunities to define patterns within big geological datasets. This in turn, facilitate a better understanding of geological structures and more precise assessment of hydrocarbon potential. These technologies provide the next advantages: 1) facilitate rapid and reliable interpretation of complex bigdata; 2) reduce human bias; 3) support the creation of integrated field models. To sum up, digital technologies have become a huge part of modern exploration industry and tool for enhancing industry efficiency (Abetov et al., 2025).

One especially promising area is lithological analysis, which plays a vital role in reservoir modeling and hydrocarbon potential assessment. ML significantly increase the lithological data processing and as a result improving classification and accuracy of interpretation (Abdimanap et al., 2024). These technologies are applied for lithotype recognition, reservoir property prediction, and identification of productive intervals. Consequently, making this approach essential tools for both mature and prospective fields.

Among supervised ML methods, the Random Forest (RF) algorithm considering as a reliable and accurate approach for processing geological, geophysical, and petrophysical bigdata. One of the main reasons is its feature importance assessment. In addition, RF has advantage as a robustness against overfitting. RF can uncover complex nonlinear relationships between rock parameters and lithological types. This feature enabling delivering stable and interpretable results with noisy/incomplete data (Kim et al., 2018; Liaw and Wiener, 2002; Breiman, 2001).

Comparing with unsupervised ML methods such as k-means or principal component analysis (PCA) tools, supervised ML uses labeled information (for example: lithotypes, facies, etc.). Subsequently, this improves the accuracy and reliability of outcome results. This makes supervised learning valuable tool for constructing detailed geological models and predictive systems with validation based on real data (Verma et al., 2016; Zhang et al., 2019).

The integration of supervised learning methods in lithological analysis enhances the reliability of interpretations, streamlines the identification of reservoirs and anomalous zones, and reduces decision-making time in oil and gas exploration and geological modeling. At the same time, the core image analysis remains a promising technique in lithology characterization (Abdimanap et al., 2024), this research takes an alternative approach of applying RF for classification lithotypes based on density, porosity, and permeability. Our research focuses on core material recovered from an oil field located at the southeastern board of the Precaspian Depression, a geologically complex region that serves as the central focus of this investigation.

The study addressed several tasks:

- Development of Python scripts using Scikit-learn / Pandas ML libraries for data preparation, training of the model, and performance assessment on the test petrophysical dataset;
- Implementation of an intuitive web-application interface using Streamlit to enable visualization;
- Training, hyperparameter tuning, and validation of the RF model.

Methods and definitions. The RF algorithm constitutes a robust supervised ML technique developed for regression tasks. Its principal strength derives from an ensemble strategy that aggregates predictions across a large number of individual decision trees, thereby generating outcomes that are substantially more accurate and resilient to overfitting than those obtained from any conventional single-model approach (Adeeyo, 2022).

Due to the number of trees in the ensemble increases, the generalization error converges toward a limit. Ultimately, the predictive accuracy of RF model is governed by two factors: 1) the individual strength of each tree in capturing underlying patterns; 2) extent of correlation among the trees themselves (Breiman, 2001).

The general architecture of a RF model is illustrated in Figure 1.

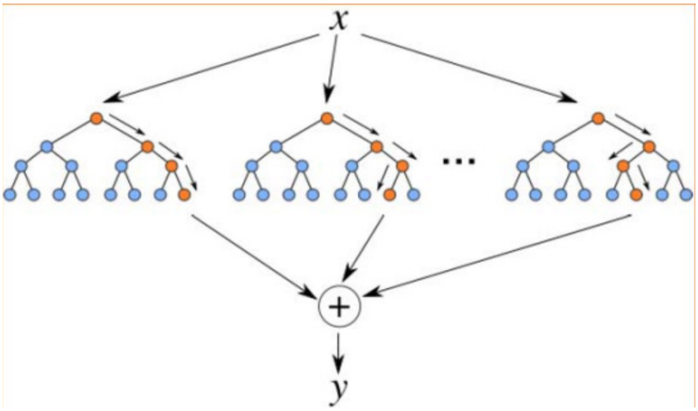


Figure 1 – Random Forest model (Adeeyo, 2022)

RF algorithm is one of the most robust and widely used ML methods for solving classification and regression problems. Because it demonstrates high accuracy while processing complex and nonlinear data. This makes it particularly valuable in geosciences and petrophysics (Adeeyo, 2022; Zhang et al., 2019).

RF achieves high accuracy and resistance to overfitting using random subsets of features and training data. For the tasks requiring high precision and overfitting resilience as a lithofacies classification, RF techniques are suitable (Abetov et al., 2025).

This approach is based on constructing a set of independent decision trees, where each tree trained on a random set input data and a random selection of features. Once the individual trees have been fully constructed, the ensemble arrives at its final prediction either through simple averaging in regression settings or by means of majority voting in the case of classification tasks. This collective aggregation mechanism substantially reduces overfitting of the model (Breiman, 2001; Liaw and Wiener, 2002).

The effectiveness of algorithm is largely determined by the law of large numbers – as the number of trees increases, the model becomes more stable and accurate. Additionally, the out-of-bag (OOB) evaluation mechanism allows empirical assessment of the model's quality without requiring a separate test dataset, which is especially valuable with limited data volumes (Verma et al., 2016; Oshiro et al., 2012).

In practice, RF is successfully used to solve geological problems: automated lithological classification, prediction of reservoir properties, permeability estimation, and evaluation of other petrophysical parameters from core and well log data (Kim et al., 2018; Zhang et al., 2019; Qi et al., 2021).

To implement RF algorithm, we used Scikit-learn library function: model = RandomForestClassifier(…). The Streamlit library was used to visualize and deploy web applications. Streamlit is an open-source Python library specifically designed for rapid development of interactive web interfaces for ML tasks.

One of the advantages of this framework is capacity to enable the rapid development of fully functional and visually engaging interfaces while demanding a minimal code (NewTechAudit, 2021).

Input data. The initial dataset for this investigation was obtained from core samples of an oil field located on the southeastern board of Precaspian Depression.

More than 10 wells were drilled at the field with core sampling, including exploration, appraisal, and production wells. The total core drilling footage was approximately 800 meters, with 40% core recovery.

ML study involved 73 core samples from Middle Jurassic sediments, lithologically represented by alternating gray-colored sandy-shaly sediments. To a lesser extent, carbonaceous clays and layers of brown coal are found. Their total thickness ranges from 438 m to 450 m.

The reservoirs of the productive Middle Jurassic horizon are composed by siltstones, sandstones, and sands. The seals are represented by the next formations: clays with thin interlayers of sandstone, sand, and silt.

In the table 1 represented core data from the productive intervals (Middle Jurassic). This samples includes the thickness of horizons, drilled footage in the pay zone, actual core recovery, and percentage relative to the drilled footage. The total drilled footage - 211.41 m, core recovery - 80.57 m (38.11%). The highest core recovery (100%) was recorded in the II Mid-Jur-2 hor. and III Mid-Jur-1 hor. intervals, while the lowest (3.13%) was observed in the II Mid-Jur-1 hor. interval.

Table 1. Drilled footage and core recovery in productive Middle Jurassic reservoirs

Horizons	**Horizon thickness, m**	**Core selection in the pay zone**		
		Drilled footage	**Core recovery (out of drilled footage)**	
		m	**m**	**%**
IV Mid-Jur -2 hor.	5,01	5,01	-	-
IV Mid-Jur -3 hor.	44,39	6,2	0,4	6,45
II Mid-Jur -1 hor.	25,08	25,08	7,78	31,02
II Mid-Jur -2 hor.	3,63	3,63	-	-
III Mid-Jur -1 hor.	9,16	7,81	4,81	61,59
II Mid-Jur -1 hor.	26,11	26,11	12,11	46,38
II Mid-Jur -2 hor.	6,12	5,28	-	-
II Mid-Jur -1 hor.	27,07	26,27	7,5	28,55
II Mid-Jur -2 hor.	3,27	3,27	-	-
III Mid-Jur -1 hor.	17,05	14,51	4,5	31,01
II Mid-Jur -1 hor.	27,59	17	3,5	20,59
II Mid-Jur -1 hor.	24,56	8	0,25	3,13
II Mid-Jur -1 hor.	26,68	18	2	11,11
II Mid-Jur -1 hor.	26,5	26,5	19,98	75,40
II Mid-Jur -2 hor.	8,81	8,81	8,81	100,00
III Mid-Jur -1 hor.	10,82	1,43	1,43	100,00
IV Mid-Jur -1 hor.	31,13	8,5	7,5	88,24
Total	**322,98**	**211,41**	**80,57**	**38,11**

Laboratory studies of core samples provided key petrophysical and lithological characteristics. This data includes reservoir type, density, total and effective porosity, oil saturation, grain size distribution, carbonate content, clay content, and gas permeability.

For ML model aimed to automated lithotype classification, were selected the most informative parameters – density, effective porosity, and permeability, due to their high sensitivity to lithological variations and widespread use in petrophysical interpretation tasks (Kim et al., 2018; Verma et al., 2016).

The training dataset included data from core samples, each containing values for the specified parameters and labeled by rock type. This provided the necessary foundation for supervised learning – in this case RF algorithm (see Table 2). The diversity in density, porosity, and permeability values within the training dataset allowed for coverage of a wide range of lithological varieties, which was crucial for improving generalization capability of the model.

Table 2. Input data for training model using RF

Depth, m	Density, g/cm3	Porosity, %	Permeability, mD	Rock type
1735,3	2,16	22	25	Sandstone
1736,6	2,05	25,7	16	Siltstone
1736,7	2,14	23	33	Siltstone
1737,2	2,46	13,7	5,5	Sandstone
….	….	….	….	….
1882,49	2,05	25,9	32,8	Sandstone
1882,6801	2,1	20,6	16,8	Sandstone
1883,1412	2,06	22,3	37	Sandstone
2100,5	2,13	22,08	7,75	Siltstone

According to the analysis results [Cao, 2023], there is a consistent inverse correlation between rock density and permeability, caused by changes in porosity. This relationship demonstrates the next relationship when rock density increases, its porosity decreases, which leads to reduced permeability.

Such interdependence becomes significant while predicting reservoir properties of terrigenous deposits on the southeastern board of the Precaspian Basin. Whereas, the accurate lithological differentiation is critical for building reliable geological models and planning efficient field development.

Of particular interest is the interdependence between porosity and permeability, as it is most closely related to the reservoir potential of rocks. In this context, density, porosity (effective), and gas permeability parameters can serve as informative indicators of lithotype, especially during application of ML methods for automated rock classification (see Figure 2).

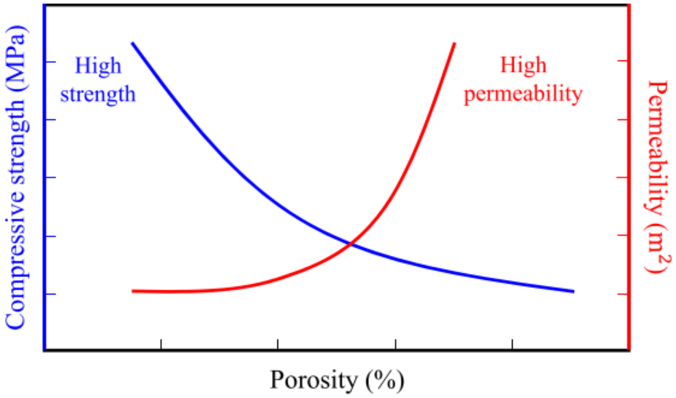
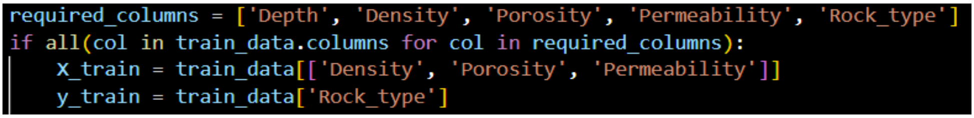


Figure 2 – Dependence of changes in porosity, permeability, and strength (Cao, 2023)

Thus, density, porosity, and permeability can be considered as key diagnostic parameters for reservoir type identification. Their integrated analysis not only enhances the accuracy of lithological classification but also provides a basis for evaluating reservoir properties, which is particularly crucial for building geological and hydrodynamic models. Furthermore, application of these parameters into ML algorithms assure robust rock differentiation despite multidimensionality and incomplete input data.

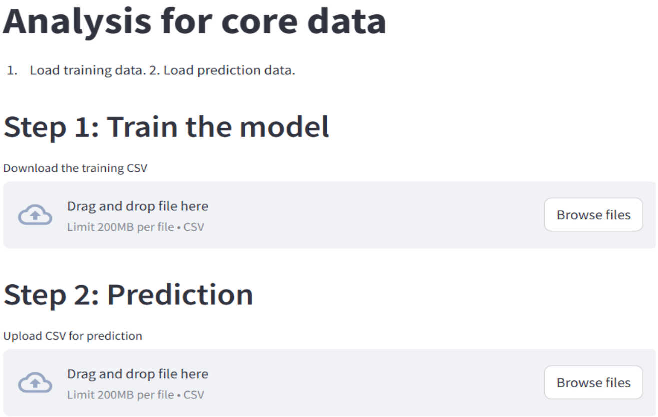
Classification of lithotypes using the Streamlit application. To ensure proper loading and subsequent processing of core petrophysical data, was implemented a format-logical control (FLC) module (see Figure 3). The FLC is designed to detect errors and inconsistencies related to format requirements. This allows to apply established data processing business rules in the framework (Леонов, 2023).



```
required_columns = ['Depth', 'Density', 'Porosity', 'Permeability', 'Rock_type']
if all(col in train_data.columns for col in required_columns):
    X_train = train_data[['Density', 'Porosity', 'Permeability']]
    y_train = train_data['Rock_type']
```

Figure 3 – FLC (part of the Python-based code)

The model supports data in CSV format, which uploads containing mandatory fields such as depth, density, effective porosity, permeability, and rock lithotype (Figure 3). After FLC procedure, the dataset automatically split into training and validation datasets. The algorithm was trained on the training dataset, after which the trained model was used to predict the target variable (lithotype) on the test dataset. Performance of the model was evaluated by comparing predicted with actual values. This evaluation applies special metrics, including accuracy, recall, F1-score, and etc [Adeeyo, 2022].



Analysis for core data

1. Load training data. 2. Load prediction data.

Step 1: Train the model

Download the training CSV

Step 2: Prediction

Upload CSV for prediction

Figure 4 – Web application interface (based on Streamlit)

Figure 4 shows the interface of developed web application using the Streamlit library. This framework designed for rapid implementation of interactive analytical systems. The interface includes the next stages:

1) Training phase – uploading a training dataset (maximum file size: 200 MB) followed by model construction;

2) Prediction phase – uploading new dataset to predict lithotype.

Research results. The research concentrated on two sedimentary rock types – sandstone and siltstone. These parameters proved as a precise evaluation of the storage capacity and the flow characteristics of the reservoirs.

The dataset was structured, where each sample contain precise lithotype labels alongside corresponding values of petrophysical parameters. This facilitates effective model training by linking input to target classes.

Thanks to the well-organized dataset, the model was able to uncover strong statistical correlations between petrophysical characteristics and lithological classes. This resulted in high accuracy for automated well log interpretation and improved confidence in the evaluation of geological formations (see Figure 5).

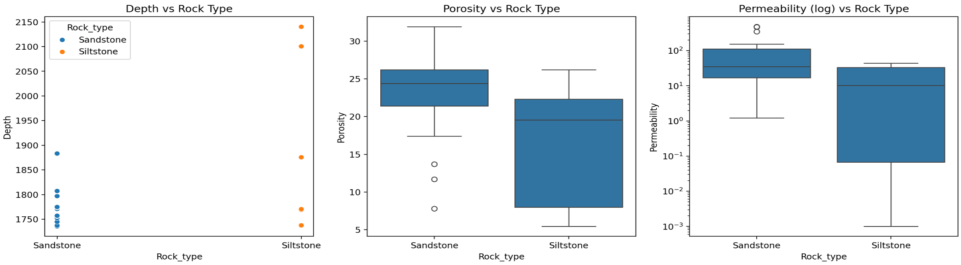
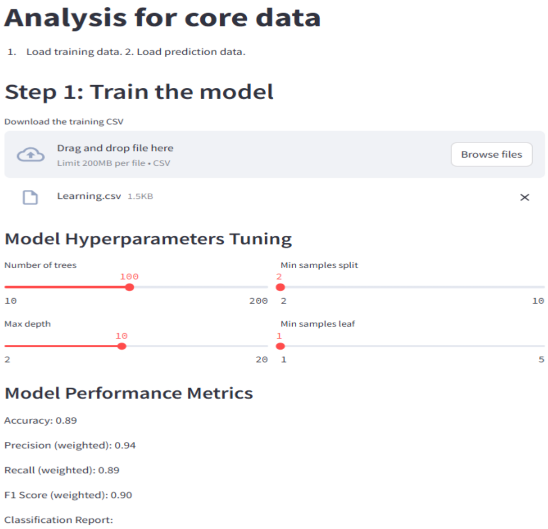


Figure 5 – Rock properties (trained data)

Figure 6 displays the interface of web application developed using Streamlit library for configuring RF model hyperparameters. Web application provides a user-friendly tool for interactive ML model tuning. This provides RF adaptation to any input data characteristics.



Analysis for core data

1. Load training data. 2. Load prediction data.

Step 1: Train the model

Download the training CSV

Drag and drop file here
Limit 200MB per file • CSV

Learning.csv 1.5KB

Model Hyperparameters Tuning

Number of trees: 100 (10–200)

Min samples split: 2 (2–10)

Max depth: 10 (2–20)

Min samples leaf: 1 (1–5)

Model Performance Metrics

Accuracy: 0.89

Precision (weighted): 0.94

Recall (weighted): 0.89

F1 Score (weighted): 0.90

Classification Report:

Figure 6 – Setting the hyperparameters of the RF

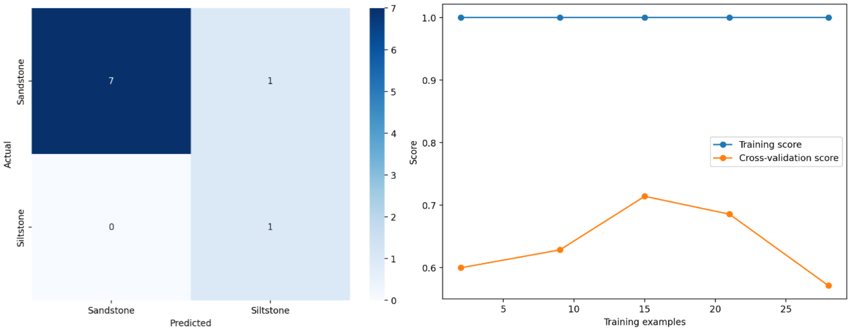
The web interface enables to set hyperparameters of the RF, among them:

- *Number of trees* – which determines the total number of trees in the ensemble. Increasing this value (e.g., to 100) improves model robustness against noise and reduces overfitting. However, it also increases training time and computational costs.
- *Min samples split* – sets the minimum number of samples required to split a node. Setting the minimum number of samples required to split an internal node at a value of 2 grants the model the highest possible granularity of partitioning. Nevertheless, such splitting brings a risk of overfitting.
- *Max depth* – limits the maximum depth of each decision tree, controlling model complexity. A value of 10 provides optimal balance between model accuracy and generalization capability. Excessive depth increases overfitting risk, while insufficient depth may cause loss of significant patterns. Alternatively, *max features* can regulate tree complexity by limiting the number of features considered for each split.
- *Min samples leaf* – determines the minimum number of samples required in leaf. Setting this to 1 maximizes model flexibility for capturing rare data patterns. However, higher values are recommended for noisy datasets to improve model robustness and generalization performance.

The interface allows real-time visualization of hyperparameter influence on model behavior, fostering a more deliberate approach to model training and optimization. This methodology enhances modeling transparency and improves the effectiveness of ML applications in geological objectives.

During configuring the hyperparameters of the model, were obtained the following quality indicators:

- *Accuracy*: 0.89 – proportion of correct predictions among all cases;
- *Precision*: 0.94 – ability of model to avoid false positives;
- *Recall:* 0.89 – completeness of model for selecting required cases;
- *F1 Score:* 0.90 – harmonic mean of precision and recall, which means overall model balance.



(a) (b)

Figure 7 – RF models outcomes: a) outcome matrix; b) learning curves (*blue line – learning score; orange line – cross-validation score*)

Figure 7 (a) demonstrates matrix of classification results. It shows actual versus predicted lithological types. In the given example, the model misclassified a “Sandstone” sample as “Siltstone”.

This error reflects a typical problem in the task of classifying sedimentary rocks due to the overlap or proximity of their petrophysical properties such as porosity, permeability and density. These characteristics may have similar values for different lithotypes, especially in transitional facies, which makes it difficult to accurately differentiate even for advanced ML algorithms.

In the figure 7 (b) represented graph of model quality versus training dataset size. It illustrates the behavior of training score and cross-validation score. The vertical axis represents values ranging from 0.6 to 1.0, and the horizontal axis shows the number of training samples.

It can be observed that as the number of training samples increases, cross-validation score improves. It shows reduced overfitting and enhanced model generalization.

This behavior is typical for models, sensitive to training data volume and highlights the importance of having a sufficient number of representative samples for training models for lithological classification tasks.

Discussion. In the proposed algorithm, the convergence of training and validation curves (Figure 7b) as the training data volume increases reflects a healthy learning process – characteristic of models with reduced overfitting and improved generalization. This behavior suggests the model is learning stable, underlying patterns rather than simply memorizing the training data.

The progressively narrowing gap between the training and cross-validation score indicates increasing robustness and reliability of the model. As more data is introduced, signaling the model's growing capacity to generalize effectively to unseen datasets (Goodfellow et al., 2016; Géron, 2019).

Such convergence is particularly important in geological applications, where predictive models must remain effective when applied to new core datasets with variable properties (Bishop, 2006). In this case, high values of both metrics (approaching 0.9–1.0 with maximum training data) confirm the suitability of the model architecture and hyperparameters in capturing the complex relationships between features and lithotypes.

The use of learning curves as a diagnostic tool is a well-established practice in ML. Overall model performance continues to improve as more training samples are supplied, the rate of that improvement gradually tapers off. Such behavior represents a classic hallmark of classification tasks (Domingos, 2012).

Feature selection plays an important role in prospective of core classification tasks. Different petrophysical parameters contribute to predictive accuracy. This is essential for building a robust models.

Gini metric is used to represent the importance of features in RF:

$$Importance\ (X_m) = \frac{1}{N_T}\sum_{T}\sum_{t\epsilon T:\vartheta(S_t)=X_m} p(t)\Delta i(s_t, t) \qquad (1)$$

This is particularly relevant for comprehensive core petrophysical analysis data, where numerous interrelated parameters are measured. Feature importance analysis helps focus on key essential characteristics for differentiating lithological types in the southeastern board of the Precaspian Depression (Kim et al., 2018).

Figure 8 demonstrates the petrophysical parameters used for rock classification: density, permeability, and porosity. These parameters were used as input features for RF model, with their relative importance assessed using the Gini metric – an indicator used to evaluate the performance of classification models, particularly in determining petrophysical properties. It is closely related to the ROC AUC (Area Under the Receiver Operating Characteristic Curve) metric, which reflects the ability of the model to distinguish between classes. The higher Gini value, the better the model separates, for example, productive intervals from non-productive. Such dataset allows the model to differentiate lithological rock types based on quantitative filtration-capacity properties.

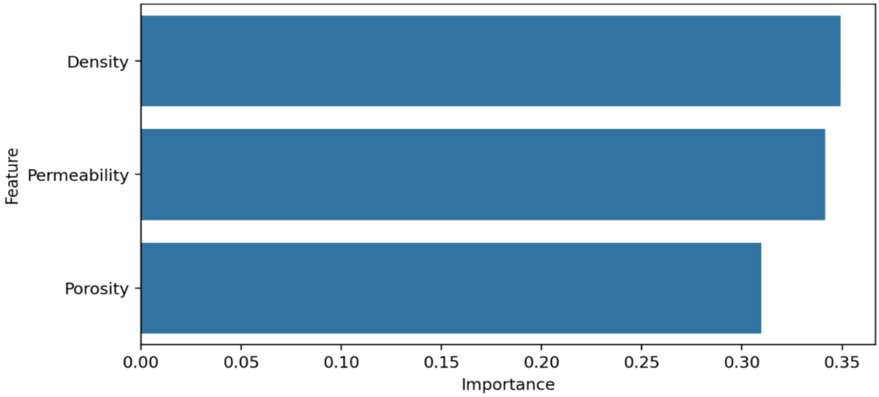


Figure 8 – Importance of functions (density, permeability, porosity)

After loading the training data and training the model, the web application provided the capability to determine rock type based on known petrophysical parameters such as porosity and permeability. Figure 9 presented graphs illustrating the performance of the model on the validation dataset.

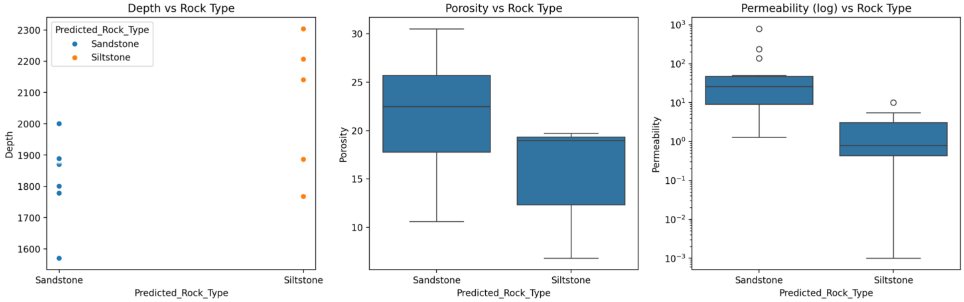


Figure 9 – Rock properties based on validation data

Looking at the model's results, it was clear that the RF split sandstones from siltstones using petrophysical properties. The model kept value ranges that matched each lithological type pretty well, and porosity stood out as the best way to split them.

Additionally, the use of a logarithmic scale for permeability visualization provided enhanced contrast. This effectively highlight filtration differences that remain obscured on a linear scale, for instance in low-permeability zones.

The comparison of predicted versus actual lithotype labels showed a high degree of consistency. This affirms the model's accuracy and ability to generalize information to unseen data. This indicates that the RF algorithm was not merely memorizing the training set but was able to identify underlying, stable patterns in the geological data – a key criterion for reliable predictive modeling in subsurface studies.

Importantly, the visualization of validation results also revealed transitional zones where petrophysical parameters of different lithotypes overlapped. These boundary areas were associated with a higher probability of misclassification. Far from being a limitation, this observation offers valuable feedback for iterative model improvement. These ambiguous zones can be targeted for threshold optimization, additional feature extraction, or refinement of model architecture – all of which can lead to improved performance in complex reservoir settings.

Overall, this integrated approach strengthened model resilience in conditions of geological uncertainty. This method makes RF a valuable tool for real-world applications in reservoir characterization and exploration decision-making.

Conclusions. The study robustly demonstrates the efficiency of RF algorithm for automating lithological classification based on core-derived petrophysical data from the southeastern board of the Precaspian Depression. This region includes different rock types, a complicated layout of reservoirs, and mixed lithofacies. It makes AI/ML applications necessary to ensure consistent and reproducible results in reservoir characterization.

The investigation utilizes core samples from wells located within this geologically complex setting. To operationalize the methodology, we have developed Python-based web application. This approach integrates Scikit-learn for model construction and assessment, Pandas for preprocessing, and Streamlit to deliver an interactive user interface for results visualization.

The modelling workflow includes the next stages: 1) data ingestion, 2) normalization of petrophysical parameters, 3) handling of missing values, and 4) restructuring datasets suitable for supervised ML. Model development included training the RF classifier with systematic hyperparameter optimization. It was able using cross-validation and grid search strategies to identify the optimal combination of model parameters.

The model's performance was rigorously assessed using accuracy, precision, recall, and F1-score. This metrics provide a multi-dimensional understanding of classification reliability. A key strength of the approach in the use of an independent validation set, excluded from the training of the RF model. This allowed for an objective evaluation of the model's generalization capability and provided clear evidence that the algorithm avoids overfitting – an essential quality for practical deployment in geological workflows.

The trained RF model achieved impressive results, with a classification accuracy of 0.89 and an F1-score of 0.90. These results indicate balanced performance in identifying correct lithotypes and minimizing false positives and negatives. These results confirm the model's ability to identify nonlinear relationships in petrophysical data and to capture subtle geological features that may be overlooked in manual interpretation.

The feature importance analysis, performed using the Gini approach, revealed that porosity and permeability are the most influential parameters. These parameters are discriminators between sandstones and siltstones. Moreover, the use of a logarithmic scale for permeability significantly enhanced the ability to distinguish low-permeability zone. This was particularly helpful in delineating tight formations and flow barriers – critical aspects of reservoir modeling.

Visual comparison between predicted and actual lithotype labels showed strong agreement, confirming the algorithm's predictive capacity. However, some transitional zones where petrophysical signatures of different lithotypes overlap were identified as regions of increased classification uncertainty. These areas are valuable targets for further model refinement, such as feature engineering, threshold calibration, or even integration of additional data modalities, including mineralogical, geochemical, or image-based parameters.

One important part of this study is building web application with Streamlit framework. This user interface supports real-time visualization of classification results, feature contributions, and real-time model tuning. These tools act as a useful link between complex data science methods and the everyday work of geologists and reservoir engineers.

From a practical view, this method offers quick and reliable way to classify lithology using real core data. It significantly reduces interpretation time, minimizes subjectivity, and ensures consistent results. Moreover, main advantage is that this application useful in the early stages of field development, appraisal drilling, and when making exploration decisions.

In the future we will continue to work focusing on the next directions:

- *Expand the classification* in order to include a wider range of lithotypes. It will include clay-rich, carbonate, and mixed lithologies, common in transitional depositional environments;
- *Integration of well log data* (gamma-ray, density, resistivity, and sonic logs) to allow spatial extrapolation of core-based interpretations. This will allow to develop *multi-scale hybrid ML models;*
- Developing tools for *uncertainty quantification* using the next methods such as Monte Carlo dropout, Bayesian inference, or ensemble variance;
- To conduct benchmark of RF performance against other supervised ML

techniques, such as *XGBoost, Support Vector Machines, and LightGBM*, in order to investigate their performance;

- Exploring *deep learning approaches* (e.g., convolutional neural networks) for automated interpretation of core images or thin section scans. It will be helpful in cases where quantitative petrophysical data is limited or incomplete.

By combining geologically meaningful features with robust ML frameworks, study makes a contribution to digitization of exploration workflows while simultaneously establishing a firm methodological foundation for the future development of intelligent geological systems. The proposed approach bridges the gap between raw data and actionable geological insights, thereby enabling more informed and more accurate decision-making in reservoir characterization.

References

Abdimanap G.S., Bostanbekov K.A., Alimova A.N., Saliev N.B., and Nurseitov D.B. (2024). Klasterizacija litotipov na osnove vizual'nyh priznakov kerna s ispol'zovaniem svertochnyh nejronnyh setej i K-Means [Lithotype clustering based on visual core features using convolutional neural networks and K-Means]. Kazakhstan Oil and Gas Industry Bulletin, 6(2). – P. 25-38. doi.org (in Russian).

Abetov A.E., and Yessirkepova Sh.B. (2025). Iskusstvennyj intellekt dlja prognozirovanija regional'nogo neftegazovogo potenciala Juzhnogo Ustjurta s ispol'zovaniem kompleksa geologo-geofizicheskih dannyh [Artificial Intelligence for Regional Hydrocarbon Potential Prediction in South Ustyurt Region Using Geological and Geophysical Data Complex]. Oil and Gas, 2. – P. 17-37. (in Russian).

Abetov A.E., Seitzhanov A.K., and Samenov Ye.R. (2025). Application of machine learning methods and neural networks in the objectives of lithofacies mapping and reservoir properties assessment: analysis and selection of methods. ANAS Transactions, Earth Sciences, 1/2025. – P. 42-51. doi.org (in Eng.).

Adeeyo Y. (2022). Random forest ensemble model for reservoir fluid property prediction. SPE Nigeria Annual International Conference and Exhibition, Lagos, Nigeria. SPE-212044-MS. doi.org (in Eng.).

Bishop C.M. (2006). Pattern recognition and machine learning. Springer. (in Eng.).

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

Cao C. (2023). Prediction of concrete porosity using machine learning. Results in Engineering, 17, Article 100794. doi.org (in Eng.).

Domingos P. (2012). A few useful things to know about machine learning. Communications of the ACM, 55(10). – P. 78-87. https://doi.org/10.1145/2347736.2347755 (in Eng.).

Géron A. (2019). Hands-on machine learning with Scikit-Learn, Keras, and TensorFlow (2nd ed.). O'Reilly Media. (in Eng.).

Goodfellow I., Bengio Y., and Courville A. (2016). Deep learning. MIT Press. (in Eng.).

Kim A., Park S., and Lee K. (2018). Lithofacies classification using machine learning and well log data. Journal of Petroleum Science and Engineering, 171. – P. 682-696. https://doi.org/10.1016/j.petrol.2018.08.002 (in Eng.).

Kim Y., Hardisty R., Torres E., and Marfurt K.J. (2018). Seismic facies classification using random forest algorithm. SEG International Exposition and 88th Annual Meeting. (in Eng.).

Kuhn M., and Johnson K. (2013). Applied predictive modeling. Springer. (in Eng.).

Leonov E.G. (2023). Realizacija processa formatno-logicheskogo kontrolja i obnovlenija regional'nogo registra prikreplennogo naselenija v edinoj gosudarstvennoj informacionnoj sisteme zdravoohranenija [Implementation of format-logical control and update process for regional attached population registry in unified state healthcare information system]. Information Technologies in Healthcare: Proc. of the 7th Int. Sci. Conf. (pp. 45–52). Rostov-on-Don: SFU. (in Russian).

Liaw A., and Wiener M. (2002). Classification and regression by randomForest. R News, 2(3). – P. 18-22. (in Eng.).

NewTechAudit. (2021). Streamlit. Poisk kratchajshego puti [Streamlit. Search for the shortest path]. Habr. https://habr.com/ru/articles/567100/ (in Russian).

Oshiro T.M., Perez P.S., and Baranauskas J.A. (2012). How many trees in a random forest? Machine Learning and Data Mining in Pattern Recognition. Springer, Berlin, Heidelberg. (in Eng.).

Qi J., Zhao T., Wang H., and Xu H. (2021). Lithology identification using machine learning based on logging and core data: Case study from the Bohai Bay Basin, China. Journal of Petroleum Exploration and Production Technology, 11(3). – P. 1037-1050. https://doi.org/10.1007/s13202-020-01090-2 (in Eng.).

Raschka S., and Mirjalili V. (2019). Python machine learning (3rd ed.). Packt Publishing. (in Eng.).

Verma S., Ghosh S., and Tiwari N. (2016). Comparison of supervised and unsupervised machine learning approaches for lithofacies classification. Journal of Applied Geophysics, 131. – P. 135-145. https://doi.org/10.1016/j.jappgeo.2016.06.007 (in Eng.).

Verma S., Zhao T., Marfurt K.J., and Devegowda D. (2016). Estimation of total organic carbon and brittleness volume. Interpretation. (in Eng.).

Zhang R., Yin X., and Wu X. (2019). Application of supervised machine learning algorithms in lithology identification: A case study from the Ordos Basin, China. Interpretation, 7(3). – T377–T389. https://doi.org/10.1190/INT-2018-0219.1 (in Eng.).

Publication Ethics and Publication Malpractice in the journals of the Central Asian Academic Research Center LLP

For information on Ethics in publishing and Ethical guidelines for journal publication see http://www.elsevier.com/publishingethics and http://www.elsevier.com/journal-authors/ethics.

Submission of an article to the journals of the Central Asian Academic Research Center LLP implies that the described work has not been published previously (except in the form of an abstract or as part of a published lecture or academic thesis or as an electronic preprint, see http://www.elsevier. com/postingpolicy), that it is not under consideration for publication elsewhere, that its publication is approved by all authors and tacitly or explicitly by the responsible authorities where the work was carried out, and that, if accepted, it will not be published elsewhere in the same form, in English or in any other language, including electronically without the written consent of the copyright-holder. In particular, translations into English of papers already published in another language are not accepted.

No other forms of scientific misconduct are allowed, such as plagiarism, falsification, fraudulent data, incorrect interpretation of other works, incorrect citations, etc. The Central Asian Academic Research Center LLP follows the Code of Conduct of the Committee on Publication Ethics (COPE), and follows the COPE Flowcharts for Resolving Cases of Suspected Misconduct (http://publicationethics. org/files/ u2/New_Code.pdf). To verify originality, your article may be checked by the Cross Check originality detection service http://www.elsevier.com/editors/plagdetect.

The authors are obliged to participate in peer review process and be ready to provide corrections, clarifications, retractions and apologies when needed. All authors of a paper should have significantly contributed to the research.

The reviewers should provide objective judgments and should point out relevant published works which are not yet cited. Reviewed articles should be treated confidentially. The reviewers will be chosen in such a way that there is no conflict of interests with respect to the research, the authors and/ or the research funders.

The editors have complete responsibility and authority to reject or accept a paper, and they will only accept a paper when reasonably certain. They will preserve anonymity of reviewers and promote publication of corrections, clarifications, retractions and apologies when needed. The acceptance of a paper automatically implies the copyright transfer to the Central Asian Academic Research Center LLP.

The Editorial Board of the Central Asian Academic Research Center LLP will monitor and safeguard publishing ethics.

Requirements for articles design for publication in the journal are available on the websites:
www:nauka-nanrk.kz
http://www.geolog-technical.kz/index.php/en/
ISSN 2518-170X (Online),
ISSN 2224-5278 (Print)

Managing Editor: *T. Apendiev*
Editors: *D.S. Alenov, A.Shormakova*
Computer layout: *G.D. Zhadyranova*

Signed for print: April 10, 2026
Format: 70×90 1/16. 26.5 printed sheets. Order No. 2.

«Central Asian Academic Research Center» LLP
Almaty, Shevchenko Street, 28